Task Me Anything

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https://www.task-me-anything.org

Abstract

Benchmarks for large multimodal language models (MLMs) now serve to simultaneously assess the general capabilities of models instead of evaluating for a specific capability. As a result, when a developer wants to identify which models to use for their application, they are overwhelmed by the number of benchmarks and remain uncertain about which benchmark's results are most reflective of their specific use case. This paper introduces TASK-ME-ANYTHING, a benchmark generation engine which produces a benchmark tailored to a user's needs. TASK-ME-ANYTHING maintains an extendable taxonomy of visual assets and can programmatically generate a vast number of task instances. Additionally, it algorithmically addresses user queries regarding MLM performance efficiently within a computational budget. It contains 113K images, 10K videos, 2K 3D object assets, over 365 object categories, 655 attributes, and 335 relationships. It can generate 750M image/video question-answering pairs, which focus on evaluating MLM perceptual capabilities. TASK-ME-ANYTHING reveals critical insights: open-source MLMs excel in object and attribute recognition but lack spatial and temporal understanding; each model exhibits unique strengths and weaknesses; larger models generally perform better, though exceptions exist; and GPT4O demonstrates challenges in recognizing rotating/moving objects and distinguishing colors.

1 Introduction

Benchmarks in computer vision have traditionally served to evaluate progress towards important research problems. They shepherd the research community's attention towards a specific capability by providing reproducible evaluation protocols to identify the best solution. For example, the NYUv2 benchmark has served to identify the best model for depth estimation for the last decade [82]. In a surprising twist, the role of recent benchmarks has shifted with the advent of general-purpose large multimodal language models (MLMs) [73, 74]. This shift has similarly led to the curation of general-purpose benchmarks that assess the diversity of capabilities and not any one single capability [60, 97, 52, 51, 24, 53, 21, 77, 62]. As a result, they are now less informative to the communities they are meant to serve—researchers, developers, and users.

When a developer wants to identify which models to use for their application, they remain uncertain about which benchmark results are most aligned with their specific use case. Consider a scenario where an application developer needs a model that can most accurately identify object shapes. They may find there are existing datasets such as SHAPES [4] and CLEVR [43] that contain shape-related task instances, yet the involved objects are simple geometric primitives instead of objects in the real world. Similarly, consider a team of researchers at a big technology corporation hoping to identify the limitations of their proprietary MLM. Although MLMs are released with evaluations on benchmarks like MMBench, MMMU, BLINK and SeedBench [60, 97, 52, 51, 24], their performance across these holistic benchmarks do not pinpoint which fine-grained capabilities are lacking.

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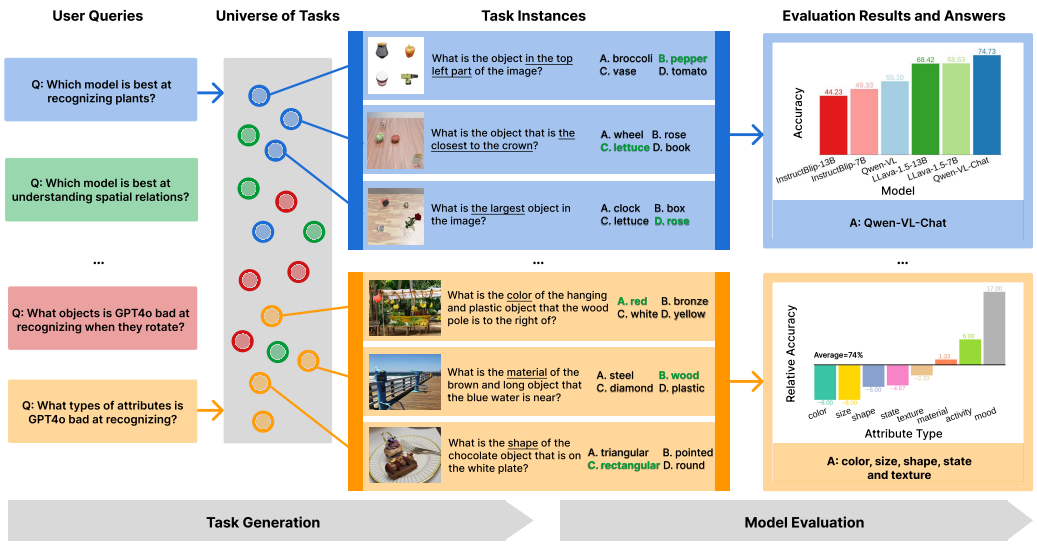


Figure 1: We present examples of user queries, corresponding task instances generated by TASK-ME-ANYTHING as well as the evaluation results on them that answer the queries.

There is a need for a principled benchmark generation process that answers task-specific user queries: "(**Q1**) Which model is the best at recognizing the shape of objects?" or "(**Q2**) what are the model's weaknesses that we can further improve on?". To actualize such a process, there are several challenges. First, we need to define an extendable taxonomy to represent the space of inputs and outputs. For example, to answer Q1, the taxonomy must include objects and their shapes. This taxonomy should be easily extendable so that future queries can evaluate new concepts. Second, the process must be able to curate a sufficient number of input-output evaluation pairs given a user query. To answer Q1, it must be able to generate thousands of images containing objects with their known shapes. Third, evaluating MLMs is computationally expensive, so the evaluation process should estimate an MLM's performance given a computation budget.

We present TASK-ME-ANYTHING, a benchmark generation engine that curates a custom benchmark given a user query (Figure 1). First, TASK-ME-ANYTHING maintains a extendable taxonomy with corresponding visual assets (*e.g.* images with scene graphs [47], 3D object assets [19], videos with spatio-temporal annotations [40], rendering softwares [15], *etc.*). It is implemented as an extendable library where new concepts and their corresponding assets and annotations can be easily added. Second, TASK-ME-ANYTHING contains programmatic task generators which sub-select from the taxonomy to curate a large number of input-output pairs. Image/videos are either from existing datasets or programmatically generated with specific configurations. With our current taxonomy, TASK-ME-ANYTHING can generate over 750 million tasks. In comparison, existing benchmarks for MLMs have fewer task instances: MME (2,194), MMBench (3,217), BLINK (3,807), MMMU (11,550), SeedBench (19,242). Programmatic task generation is not new—CLEVR [43] and GQA [39] were also programmatically generated. While their contribution is the final generated benchmark, our contribution is the benchmark generation process itself. Third, TASK-ME-ANYTHING allows users to specify a computation budget. It contains algorithms to approximate the results of user queries via predicting the model performance across a large number of input-output pairs without actually invoking the MLM on each task instance.

The current version of TASK-ME-ANYTHING's library contains $122,866$ scene graphs [39, 29] associated with $113,018$ real images and $9,848$ real videos, $1,996$ 3D object assets [20, 19] with manual annotations, can curate 28 types of tasks (counting "how many . . .?", color questions "what color . . .?", etc.), 365 object categories, 335 relationships, 655 attributes, and 14 spatial positions. With this, we extensively evaluate 13 open-source MLMs over 1M task instances and 18 open-source/proprietary MLMs over $8,400$ task instances, both generated by TASK-ME-ANYTHING. We then address the following questions: (1) "What perceptual capabilities do open-sourced MLMs still lack?"; (2) "Do all models lack the same perceptual capabilities?"; (3) "Do larger (or proprietary)

models always exhibit superior perceptual capabilities than smaller (or open-source) ones?"; (4) "What specific capabilities does GPT4O, the recently introduced proprietary MLM, still lack?".

Our analyses produce the following takeaways: (1) open-sourced MLMs exhibit strong object and attribute recognition abilities but struggle at counting, spatial and temporal understanding. (2) while most models perform similarly across different capabilities, individual models showcase different strengths and weaknesses (*e.g.*, QWEN-VL-CHAT is good at spatial relation understanding whereas INSTRUCTBLIP-7B is exceptionally good at understanding emotional relations). (3) Larger MLMs do tend to perform better than smaller ones with a few exceptions (*e.g.*, INSTRUCTBLIP-7B outperforms INSTRUCTBLIP-13B on relation understanding). (4) The best open-source MLM is on par with if not better than the best proprietary model across skills, with a nontrivial performance margin up to 7 and 8% on spatial and 3D attribute understanding. (5) We found that recognizing rotating/moving "furniture", "food", and "plants" is more challenging for GPT4O than for other object categories like animals and vehicles, likely because these objects are typically static in the real world, and GPT4O struggles more with distinguishing colors than other attributes.

2 TASK-ME-ANYTHING

Consider a user who wants to know "Which open-sourced MLM is best at recognizing objects even if the object is rotating?". TASK-ME-ANYTHING provides an interface for the user to pose such questions and provides them with an answer (Figure 2). It contains a taxonomy to symbolically represent visual content. A query identifies the relevant portion of the Taxonomy required to answer the query. It also contains task generators that create input-output pairs that test for a specific capability. The Taxonomy subset is used to select the appropriate task generator. We adopt the common input-output format used in existing benchmarks, *i.e.*, all the task instances in TASK-ME-ANYTHING contain an image/video, a question, and multiple options with one ground truth answer. MLMs will be evaluated on these generated task instances and the results will be returned back to the user. Finally, it also supports queries that ask for, not just the best performing model, but also task instances ("Find top-10 task instances that GPT4O performs the worst") or taxonomy concepts ("Find the objects that GPT4O's performance is higher than a threshold"), as well as on-budget results approximation methods for such fine-grained queries. unlike most existing procedural data systems, we design TASK-ME-ANYTHING so that the generation space of tasks can be expanded by adding new source data and/or task generator code. More details in Appendix B and C.

2.1 Taxonomy

We adopt a spatio-temporal scene graph as a representation of concepts represented in an image or video [47, 40]. In a scene graph, objects and their corresponding attributes are nodes and relationships between objects are edges. Scene graphs have already been utilized in programmatic generation of VQA task instances in datasets like GQA [39] and AGQA [29, 25]. For example, the object nodes of the scene graph can be used to create counting tasks, relationships edges can encode relative locations and generate spatial understanding tasks, and attributes can ask about color, material, physical states like rotation, etc. The scene graph representation is generic: it can be extended to incorporate concepts like lightning conditions and ask questions about the light source, illumination, and shadows [7]. In fact, we extend traditional scene graphs with 3D object assets from Objaverse [20, 19], enabling us to ask questions about any objects with available 3D models and their spatial positions, *etc.*.

2.2 Task generators

A task generator is a Python program that can generate VQA task instances given a subset of the taxonomy. It generates questions using templates of the type: "How many <target object> are there in the image?", where the <target object> can be filled with objects in the scene graph such as "telephone". Also, it programmatically produces the ground truth answer based on the scene graph. It synthesizes incorrect yet plausible options for each question [98]. For the visual input associated with every question, we use the images [39] and videos [29] annotated with scene graphs. However, scene graph data is expensive and therefore, limited. To facilitate diverse user queries, we programmatically generate images/videos from scene graph representations [10, 4]. Since image/video generation models can introduce potential errors into our evaluation pipeline, we leave the use of generative models to future work. Instead, we programmatically generate image/video layouts and render them

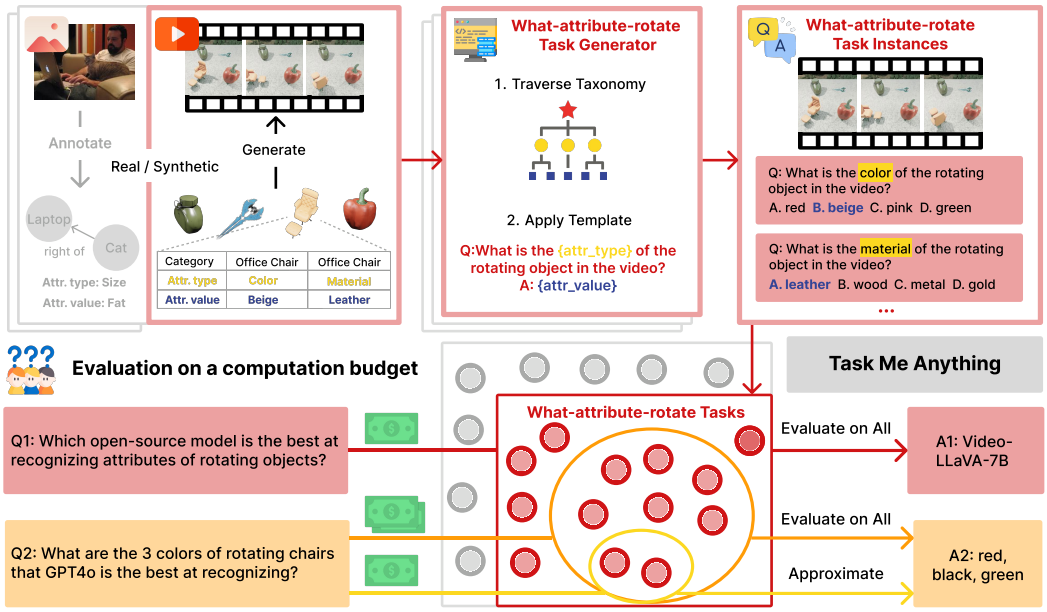


Figure 2: We present the key components in TASK-ME-ANYTHING. The top part illustrates the task generation process with an example video synthesized with 3D objects and their annotations, and the task generator for generating questions about rotating objects' attributes. The bottom part depicts the model evaluation process, which selects the relevant tasks based on the user's query and their budget and performs either full evaluation or results approximation to answer the query.

using Blender [15] with 3D object models [20, 19] via the following two approaches: 1) *2D sticker image* (abbreviated to 2D): Inspired by the SHAPES dataset [4], we position individual 2D rendering images of 3D object models in a grid (either 2x2 or 3x3) to compose an image, which is fast to generate but lack realism, *e.g.*, plausible object co-occurrences, lighting, shadows, *etc.* are absent. and 2) *3D tabletop scene* (abbreviated to 3D): To overcome the limitations of the 2D approach, we render tabletop scenes to generate images after placing the 3D object assets on the table [68]. Similarly, we generate videos and adjust the position and angle of the objects across different key frames to make objects move and rotate. Such rendered images/videos are more realistic since Blender also supports lightning and collision controls.

Concretely, we use the term *task plan* to refer to the ingredients that a task generator requires for task generation, which contain the necessary task metadata and configurations. For example, in tasks involving counting, the task plan specifies the categories of objects, their total numbers in the scene, and their positions in the image—such as two apples, one on the top right and one on the bottom left. The *task instance* then features an actual image/video, question, options, and ground truth answer tuple that comprises a single evaluation test case and is generated by a task generator with a specific task plan. One such task instance might be an image with two apples, the question: "How many apples are there in the image?", and the answer: "2". Multiple task instances can be generated from a single task plan because other elements such as the image background and types of distractor objects can be randomized, as they are not specified in the task plan. We refer to this family of task instances that can be generated by a task generator with a specific task plan as *task class* or *task*, a conceptual abstraction of all task instances derived from the same task plan. Finally, each task generator is implemented for a specific type of task, *e.g.*, the 2D how-many task generator is for generating counting tasks with *2D sticker image* images and has two major functionalities. First, it should define the schema of the task plan it can input and be able to enumerate all the possible task plans given the source data, *e.g.*, the 3D object models and annotations; Second, it can generate concrete task instances given a valid task plan.

2.3 Addressing user queries

Given the millions of task instances that TASK-ME-ANYTHING can generate, it is computationally infeasible to evaluate even a single model on the entire task space. It would also take too long to be useful for everyday users. We describe how TASK-ME-ANYTHING supports on-demand task generation and evaluation to address user queries.

Because each task generator supports generating all the task plans without generating the actual task instances and these task plans, once pre-computed, can act as a structured representation of the task space, users can leverage them to identify tasks relevant to their queries and then opt to only generate and evaluate the models on the relevant tasks. For example, image a user query "Which open-source model is the best at recognizing shapes of rotating objects?", the user can leverage the what-attribute-rotate task generator to compute all the task plans, select those related to recognizing shapes and then use them to generate actual task instances to evaluate and compare open-source models. Such a workflow enables *query-centric* task generation and evaluation, avoiding generating and evaluating the entire task space.

Fine-grained user queries. While many user queries can be simply addressed by the aforementioned workflow, we additionally support 4 types of fine-grained user queries for investigations regarding individual tasks and taxonomy concepts:

(1) *Top-K queries* enable users to request the top-K taxonomy concepts or tasks (*e.g.*, "Return the top-10 colors/tasks that LLAVA-13B struggles with").

(2) *Threshold queries* allows users to query for taxonomy concepts or tasks where model performance surpasses or falls below a given threshold (*e.g.*, "Find all the object recognition tasks that both LLAVA-NEXT-34B and GPT4O perform below 30% accuracy?").

(3) *Model comparison queries* identify where one model outperforms another by a specified margin, enabling comparative analysis (*e.g.*, "Which types of tasks does GPT4O outperform GEMINI-PRO?").

(4) *Model debugging queries* identify where a model's performance deviates from its average by one standard deviation, facilitating the ability to uncover models' inconsistent behavior. (*e.g.*, What action does VIDEO-LLAMA-2-7B struggle to recognize compared to other actions?).

Addressing fine-grained queries under a budget. These fine-grained user queries might involve a large number of tasks to generate and evaluate to obtain query results. For example, to obtain the top K tasks of a task generator that model performs the worst, we have to evaluate all the possible tasks. To address this, we draw on active learning literature [45], to implement 3 efficient query results approximation approaches for these fine-grained user queries:

(1) *Random* randomly samples a subset of task instances from the total possible for that query. MLMs are evaluated on only this subset.

(2) *Fitting* similarly samples a random subset and evaluates MLMs. The results are used to train an efficient function approximator for each MLM. This function approximator learns to predict an MLM's performance on a task, by featurizing the task-metadata—never actually generating the task instance itself. While many model choices are applicable, we adopt the Gaussian Process regressor throughout this work since it renders stable performance in preliminary studies. It uses this function to approximate the MLM's performance on the remaining task space.

(3) *Active* is similar to *fitting* but iteratively trains each function approximator using active learning. Given a smaller subset, it trains an initial function, which is then used to sample the most uncertain task instances. MLMs are evaluated on these uncertain instances; the results are used to *re-train* the functions again.

2.4 Final benchmark engine

Although TASK-ME-ANYTHING supports many different kinds of reasoning tasks, it currently focuses on visual perception capabilities. We include 28 different task templates across 5 types of visual inputs: 2D sticker images (2D), 3D tabletop scene images/videos (3D), and real images/videos

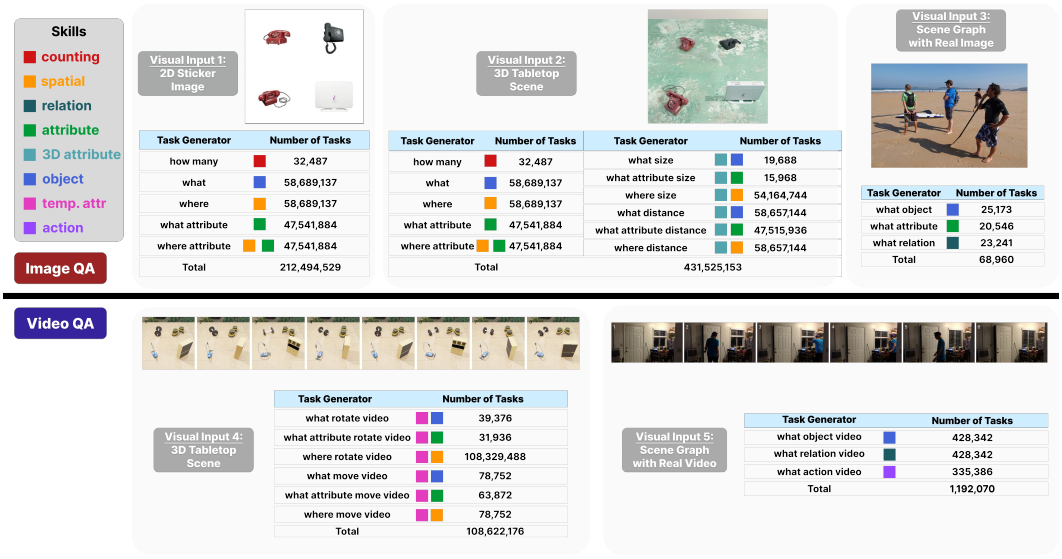


Figure 3: The statistics of generatable tasks of each task generator and example image/video in TASK-ME-ANYTHING. We each task generator with high-level perceptual skills and this collection of task generators can collectively generate over 750M VQA tasks.

with manually-annotated scene graphs. In total, it can generate over 750 million possible VQA task instances (see Figure 3 for a breakdown). We draw image scene graphs from Visual Genome [47], and video spatio-temporal scene graphs from Action Genome [40]. We also include GQA [39] and AGQA [29] for their real VQA instances. For 2D and 3D scenes, we select $1,996$ high-quality 3D objects across 337 categories from Objaverse-LVIS, the subset of Objaverse 1.0 [20] that has been annotated with LVIS [30] categories. Each 3D object was manually annotated with attributes such as color, material, shape, and visible angles. More details can be found in Appendix D.

These 28 different task generators provide a comprehensive way to evaluate visual understanding capability including object recognition, attribute recognition, relation recognition, localization, spatial reasoning, temporal reasoning, action recognition, *etc.* (Figure 3). With this diversity of potential questions, TASK-ME-ANYTHING supports the evaluation at varying desired levels of granularity

For model users, TASK-ME-ANYTHING can help decide which model to use for their needs, and for model developers, it can identify the weaknesses of models to improve. For example, a model user wanting to find the best model for distinguishing different breeds of dogs can query: "What are the top 3 models for distinguishing dogs?" Similarly, a model developer might query: "Find the spatial reasoning capabilities that all models lack?" to identify some general issues in current architecture. Or they might also query: "Which types of materials do LLAVA underperform on?" and then add the corresponding data into training to enhance LLAVA's material recognition performance.

This system is not only versatile but also scalable. By adding new task generators, assets like 3D object models, and software like Blender, DALL-E, etc., we can continuously expand its taxonomy. Updating a taxonomy of underlying capabilities is more scalable than collecting sufficient data for the rapid growth in use-cases for MLMs.

3 Evaluating MLMs using TASK-ME-ANYTHING

In this work, we extensively evaluate 13 open-source MLMs over 1M task instances and 18 open-source/proprietary MLMs over $8,400$ task instances, both generated by TASK-ME-ANYTHING, for validating TASK-ME-ANYTHING and analyses.

Model evaluation protocol. We adopt the accuracy of the model on a task to capture the model's performance. However, one task can contain numerous concrete task instances. In practice, we randomly generate n task instances for a task and then use the model's accuracy on the n task instances as a proxy of the model's accuracy on the task. For prompts used to evaluate the models,

to fairly evaluate the model's performance and enhance the robustness of the results. We use two versions of prompts: a succinct prompt and a detailed prompt. The succinct version simply adds 'Select from the following choices' between the question and the options [24], while the detailed prompt includes more instructions such as: 'Based on the image/video", and also enclose the options within parentheses (e.g., "(A) camera (B) telephone")' and ends the prompt with 'Best Option: (' to guide the model to output the option only [53]. The exact prompt template can be found in Figure 4." For option extraction, we match the model output to three types of option representations: 1) option identifier, *e.g.*, "(A)", 2) option name, *e.g.*, "camera", and 3) option identifier and name, *e.g.*, "(A) camera" in order to increase the recall of the option extraction.

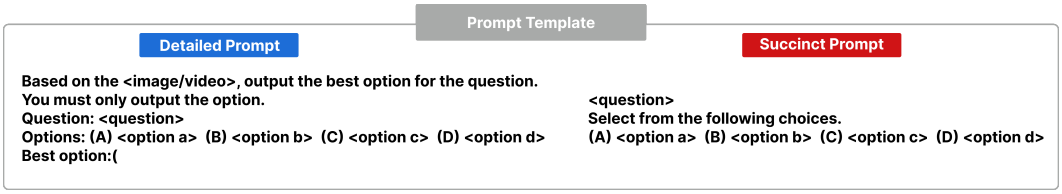


Figure 4: We adopt two distinct prompts, the detailed prompt and the succinct prompt, in our evaluation to assess models' sensitivity to different prompts.

TASK-ME-ANYTHING-RANDOM: A random set of tasks. To offer an overview of the task space of the current TASK-ME-ANYTHING, we create a random subset of 100 tasks from each task generator. For each task, we randomly generate 3 task instances, resulting in 5,700 ImageQA task instances and 2,700 VideoQA task instances. We refer to this random set as TASK-ME-ANYTHING-RANDOM, which we release as a benchmark. We evaluate 18 open-source/proprietary MLMs on this set using both detailed prompt and succinct prompt.

TASK-ME-ANYTHING-DB: A database of model evaluation results. We also randomly select over 100K tasks across all the task generators and generate 15 task instances for each task, leading to over 1M task instances in total. Then we evaluate 13 open-source MLM models on the generated task instances using detailed prompt, leading to a total number of 24,240,780 <model, task instance> evaluation pairs. We refer to this set of evaluation results as TASK-ME-ANYTHING-DB, which we use to study the query results approximation methods and release for future study of model performance prediction.

TASK-ME-ANYTHING-UI: A graphical interface for model performance investigation. TASK-ME-ANYTHING allows users to query for tasks that most resemble their application. As such, TASK-ME-ANYTHING doesn't have to be limited to a static leaderboard commonly seen with most other benchmarks. Instead, we make TASK-ME-ANYTHING's findings accessible through an interactive graphical user interface. Our interface allows users to specify their needs without writing any code. They can subselect parts of the taxonomy that best represent their application. We use the evaluation results in TASK-ME-ANYTHING-DB obtained our explorations to build a simple example interface: TASK-ME-ANYTHING-UI[2]. It consists of four tabs: the **overall** tab reports model performance across a dozen MLM across different subsets of TASK-ME-ANYTHING's taxonomy; the **task embedding** tab visualizes different task instances in a 2D space and allows users to observe model behavior across similar tasks; the **surprisingness** tab highlights tasks where a model achieves surprisingly better or worse performance compared to similar tasks; and the **query** interface supports users to conduct query-centric investigation of models' capabilities or limitations using the four types of fine-grained user queries mentioned above (Figure 5). More details can be found in the Appendix D.3.

4 Validating and ablating TASK-ME-ANYTHING

We validate the accuracy of our generated evaluated data by measuring human performance on our tasks. Then, we evaluate the different approximation methods introduced in Section 2.3 to demonstrate their effectiveness.

[2] https://huggingface.co/spaces/zixianma/TaskMeAnything-UI

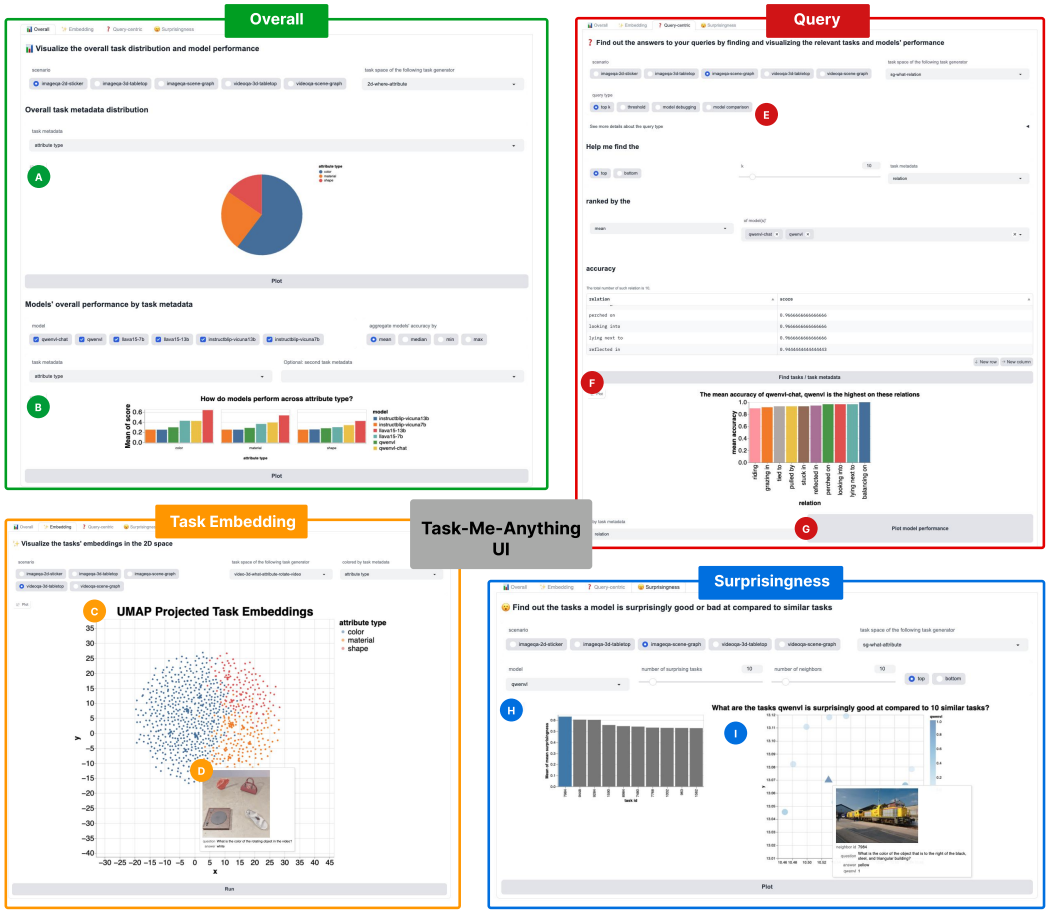


Figure 5: TASK-ME-ANYTHING-UI Interface.

Validating with human evaluation. To validate TASK-ME-ANYTHING, we first conduct a ($N = 2$) human evaluation on TASK-ME-ANYTHING-RANDOM to check the correctness of the tasks. In these random subsets, annotators achieve an accuracy of $92\% - 100\%$ for task instances from different task generators (specifically, humans perform 100% on the ImageQA 2D how-many tasks while 92% on the VideoQA 3D what-rotate tasks), indicating that our tasks are accurate and can be solved by humans. By contrast, GQA [39] and AGQA [29] report a human performance between $70\% - 84\%$.

Ablating the approximation algorithms. We evaluate the proposed query results approximation algorithms on 1,137 queries across the 4 query types (Table 1). To measure the quality of the approximation, we use the evaluation results from TASK-ME-ANYTHING-DB as ground truth query results. From Table 1, we can see that the *Active* method outperforms both the *Random* and *Fitting* methods across nearly all query types, yet there is still room for future improvement. More details of experiments and results are in Appendix F.

Table 1: The performance of query results approximation algorithms. Top-K query uses Mean Rank (MR, lower is better) and Hit Rate (HR, higher is better) as metrics, while other queries use Precision (P), Recall (R), and F1-score (F1).

Method	Top-K Query		Threshold Query			Model Compare Query			Model Debug Query		
	MR	HR (%)	P (%)	R (%)	F1 (%)	P (%)	R (%)	F1 (%)	P (%)	R (%)	F1 (%)
Random	46.81	42.30	46.88	42.48	44.05	**100.00**	24.58	37.28	**93.39**	23.27	35.04
Fitting	34.43	46.77	**47.45**	46.34	46.46	78.42	47.44	52.59	83.27	32.04	43.86
Active	**10.79**	**70.55**	47.39	**46.83**	**46.55**	89.94	**54.88**	**61.87**	89.95	**43.84**	**56.44**

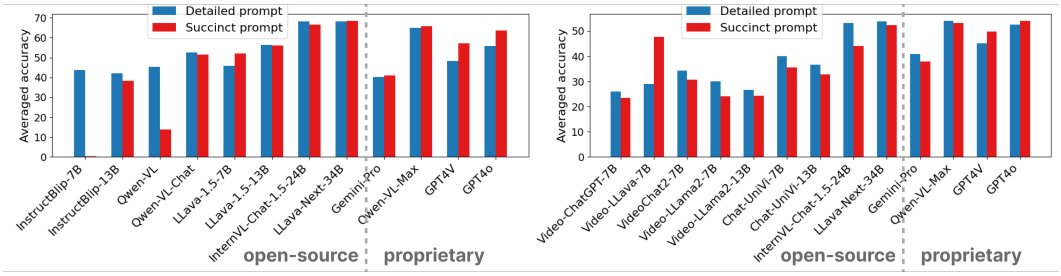
5 Analysing MLMs with TASK-ME-ANYTHING

We use TASK-ME-ANYTHING to conduct multiple analyses to highlight its different use cases, while simultaneously drawing insights about today's MLMs (More details in Appendix G). Specifically, we evaluated 18 MLMs on TASK-ME-ANYTHING-RANDOM for Query 1 and 4 and reused the evaluation results of TASK-ME-ANYTHING-DB for Query 2, 3, 5, and 6. Finally, we leverage TASK-ME-ANYTHING to provide an in-depth analysis on GPT4O as Query 7.

5.1 Query 1: How do models perform over a random subset of all possible questions?

We evaluated 18 MLMs on the TASK-ME-ANYTHING-RANDOM test set (Figure 6) to gain an overview of model performance. The detailed prompt typically yields better results; however, certain models, like GPT4V, perform much better with the succinct prompt, indicating that current models are still prompt-sensitive.

For ImageQA tasks, the latest open-sourced models, such as INTERNVL-CHAT-1.5-24B and LLAVA-NEXT-34B, perform better than popular proprietary models, achieving state-of-the-art performance, which is also shown in recent benchmarking results [16]. Notably, models like INSTRUCTBLIP-7B and QWEN-VL perform significantly better with detailed prompt than succinct prompt. For VideoQA tasks, we also evaluated larger or proprietary ImageQA models, like GPT4V, by concatenating four frames of a video into a single picture. Notably, VIDEO-LLAVA-7B perform much better with succinct prompts than other small open-source models.



(b) ImageQA (b) VideoQA

Figure 6: Model performance on the TASK-ME-ANYTHING-RANDOM, a random subset of tasks from TASK-ME-ANYTHING.

5.2 Query 2: What skills are MLMs best and worst at?

We analyze performance across different perceptual capabilities to answer: what skills are all models good or bad at? We conduct this study for both ImageQA and VideoQA tasks respectively. We find that no specific skill appears to be the best or worst across (both image and video) models (Figure 7). We see that all models struggle in spatial reasoning, counting objects, and 3D attribute understanding on ImageQA tasks, and object recognition, temporal understanding on VideoQA tasks. They perform well on object, attribute, and other relationship recognition instances. Surprisingly, we find that most MLMs perform the best at relationship understanding between objects, scoring high if not perfectly on interactional relations such as "riding", "looking into", "lying next to" etc. On the other hand, these models struggle the most in spatial reasoning in synthetic images, performing poorly especially on questions that ask about objects in the "middle", "bottom" or "back" (for 3D images) part of the image. Nevertheless, some models behave differently. For example, LLAVA-13B is worst at recognizing 3D attributes, failing at identifying the "smallest" or "closest" 3D objects correctly. Meanwhile, LLAVA-7B is best at object recognition and worst at relation understanding, struggling to understand simple actions such as "touching" that other models perform well on.

Further, TASK-ME-ANYTHING also enables us to conduct analyses of models' fine-grained skills such as recognizing a specific type of object, attribute, or relation. For example, on ImageQA tasks, we find that on average models are better at recognizing plants, understanding mood and comprehending spatial relations between real-world objects (Figure 9). Nevertheless, some models might showcase different strengths: LLAVA-13B is better at recognizing animals (Figure 9 (a)), and INSTRUCTBLIP-7B is better at understanding emotional relationships (Figure 9 (c)). On the

other hand, for VideoQA tasks, we learn that models are better at recognizing vehicles, material and understanding spatial relationships (Figures 10 and 11).

5.3 Query 3: what is the best MLM for each specific skill?

LLaVA-13B stood out as the strongest model on ImageQA tasks, achieving the best performance on all skills except for relation understanding; and Video-LLaVA-7B is the overall winner on VideoQA tasks, scoring the highest on action understanding and second or third elsewhere. Specifically, we find that LLaVA-13B performs consistently better than other multi-modal models on all skills except for relation understanding, where Qwen-VL-Chat performs better (Figure 7 (a)). On VideoQA tasks, in addition to Video-LLaVA-7B, Chat-UniVi-7B is also relatively well-rounded, positioning in the top 3 models across all skills except for Attribute understanding (Figure 7 (b)). On the other hand, while VideoChat2-7B specializes in object, attribute, and temporal attribute understanding, it falls short on Action and Relation reasoning (Figure 7 (b)).

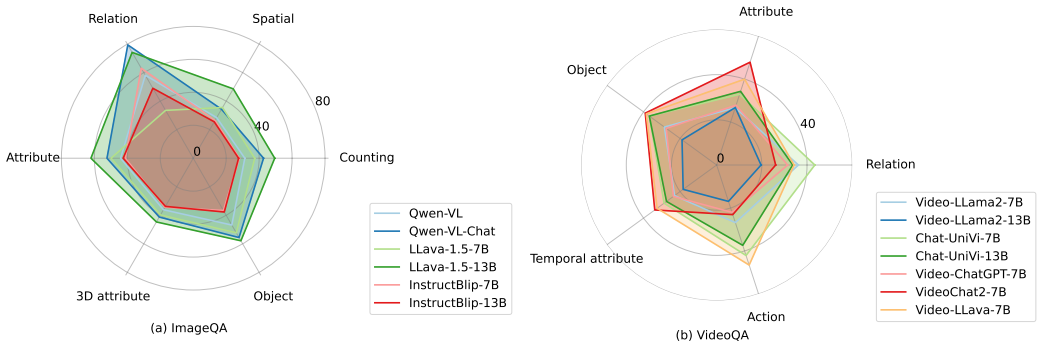


Figure 7: **Image and VideoQA, high-level skills, all models.** We plot models' performance on Image and VideoQA tasks across all skills. We learn that models are relatively good at object and attribute recognition in both Image and VideoQA and relation understanding in ImageQA but still struggle at others.

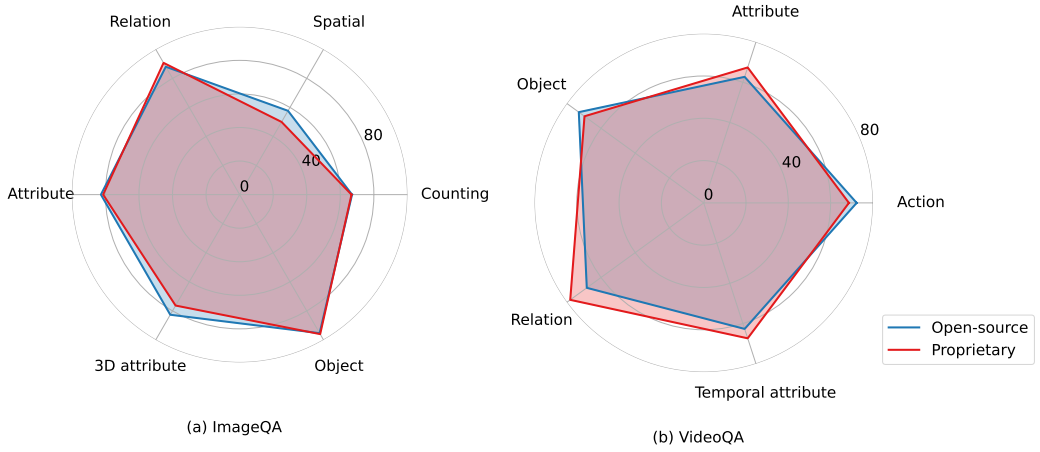


Figure 8: **Image and VideoQA, high-level skills, open-source vs. proprietary best models.** We plot the performance of the best open-source and proprietary model for each skill on ImageQA and VideoQA tasks.

5.4 Query 4: How does the best open-source model compare against the best proprietary model across skills?

Moreover, we find that on ImageQA tasks, the best open-source model (LLaVA-Next-34B on object recognition, LLaVA-13B on relation understanding and InternVL-Chat-1.5-24B else

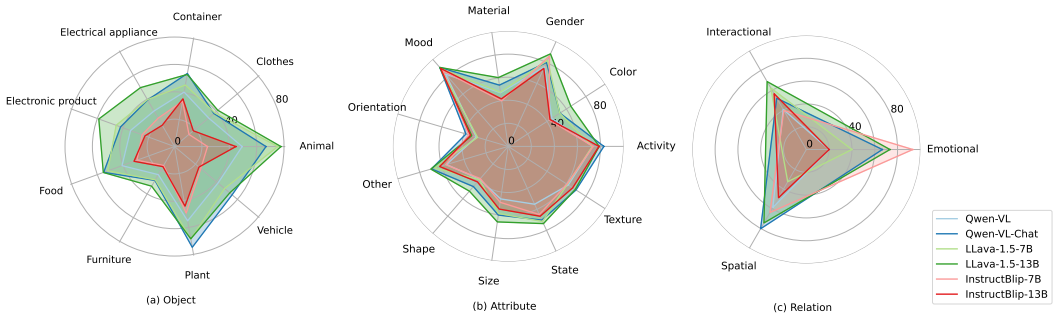


Figure 9: **ImageQA, fine-grained skills, all models.** We also analyze models' performance on ImageQA tasks across fine-grained skills and find that models are good at recognizing plants, understanding mood, and comprehending spatial relations between real-world objects on average despite differences in individual models.

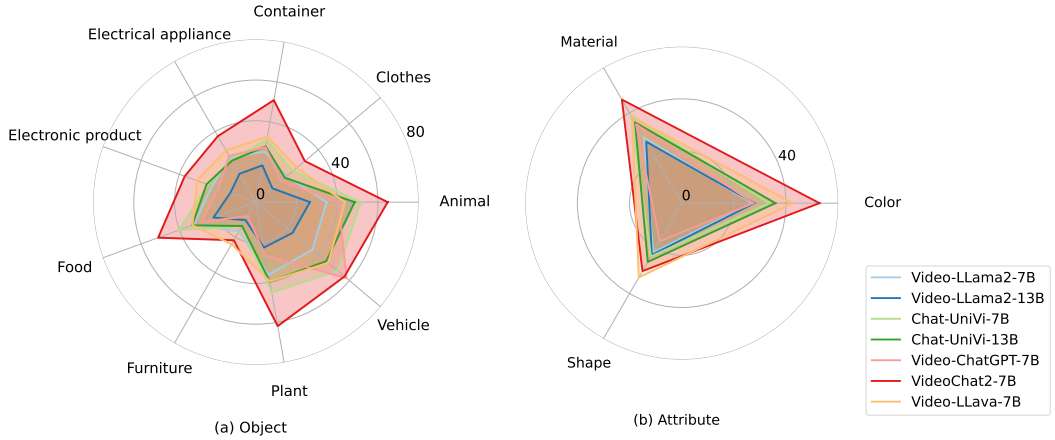


Figure 10: **VideoQA, fine-grained object and attribute skills, all models.** We present models' performance on VideoQA tasks across fine-grained skills and find that, on average, models are good at recognizing vehicles and understanding materials in videos.

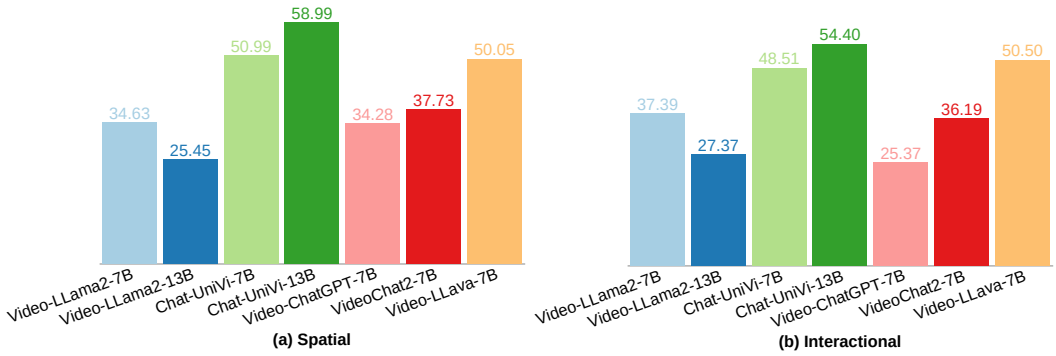


Figure 11: **VideoQA, fine-grained relation skills, all models.** On VideoQA tasks, we find that models are better at understanding spatial relations than interactional ones on average.

where) is on par with if not better than the best proprietary model (GPT4O on attribute recognition, GPT4V on counting and QWEN-VL-CHAT else where) for most skills (Figure 8). Notably, the best open-source model outperforms the best proprietary one on spatial reasoning by around 8% and 3D attribute by 7%. On VideoQA tasks, the best open-source model INTERNVL-CHAT-1.5-24B surpasses the best proprietary one QWEN-VL-MAX on object and action recognition but lags behind proprietary models by 5-10% on attribute, temporal attribute and relation understanding.

5.5 Query 5: How do small models compare against large models?

We are also interested in the relative performance of small versus large models with the same skills. On ImageQA tasks, for example, we observe that large multi-modal models collectively perform better than smaller models on ImageQA tasks (Figure 12). Nevertheless, this finding might not always hold for individual models. Through t-tests with pairs of small and large models from the same source, we find one exception: INSTRUCTBLIP-7B (μ = 0.63) significantly outperforms INSTRUCTBLIP-13B (μ = 0.49) on relation understanding with p-value $< 1e-5$ (Figure 14).

On VideoQA tasks, interestingly, we find that small models beat larger models on VideoQA tasks on average (Figure 13). We hypothesize that this is because we included some strong small video models in our evaluation. For example, we see that VIDEO-LLAMA-2-7B achieves a higher score than VIDEO-LLAMA-2-13B in all skills with p-value $< 3e-5$ (Figure 15), and CHAT-UNIVI-7B outperforms CHAT-UNIVI-13B on action and relation understanding with p-value $< 1e-5$ (Figure 16).

Figure 12: Skill comparison: small vs. large models on ImageQA.

Figure 13: Skill comparison: small vs. large models on VideoQA.

Figure 14: Skill comparison: INSTRUCTBLIP-7B vs. INSTRUCTBLIP-13B.

Figure 15: Skill comparison: VIDEO-LLAMA-2-7B vs. VIDEO-LLAMA-2-13B.

Figure 16: Skill comparison: CHAT-UNIVI-7B vs. CHAT-UNIVI-13B.

5.6 Query 6: Are models' strengths and weaknesses consistent across visual inputs?

Further, we are curious if the models' strong and weak skills are consistent across visual inputs. To this end, we look at models' performance across visual inputs for object, attribute, spatial understanding, and counting as these skills involve tasks in multiple visual inputs such as 2D and 3D. We find that for the same skill, the rankings of models remain largely consistent across visual inputs (Figure 17). We observe strong correlations (with Spearman coefficients of 0.77-0.94) between models' accuracy scores for different visual inputs in the same skill with only one exception: the video models' performance on object understanding in 3D tabletop tasks is only weakly correlated (coefficient = 0.64) with their performance in scene graph tasks. This finding suggests our definition of skills is orthogonal to visual inputs and enables us to find models' inherent strengths and weaknesses.

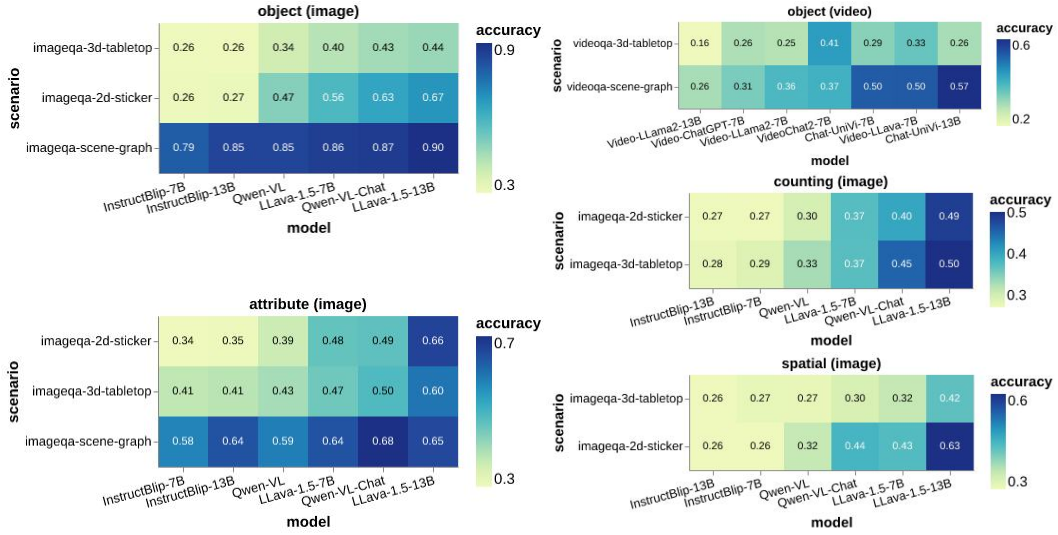


Figure 17: We present models' performance for each skill across visual inputs.

5.7 Query 7: What is today's popular proprietary model, GPT4O, bad at?

Finally, we investigate GPT4O, today's popular proprietary model: what *objects* are GPT4O bad at recognizing when rotating/moving? what *relations* are GPT4O bad at understanding? and what *attributes* of objects are GPT4O bad at recognizing? To answer these questions, we first identify task generators for each question that can generate relevant tasks to evaluate, based on which we provide both the object/relation/attribute categories and individuals that GPT4O are bad at. Note that these are just example questions, and many more of this type can be addressed by TASK-ME-ANYTHING.

Answering with object/relation/attribute categories. First, we answer these questions by comparing GPT4O's performance across different coarse-grained object/relation/attribute categories and their average, as shown in Figure 18. We can see that 1) GPT4O does not perform well in recognizing "interactional" relations in images and "spatial" relations in videos, 2) recognizing rotating/moving "furniture", "food", and "plant" is more challenging for GPT4O than other object categories such as animal and vehicle, and 3) GPT4O is worse at recognizing "color" than other attributes.

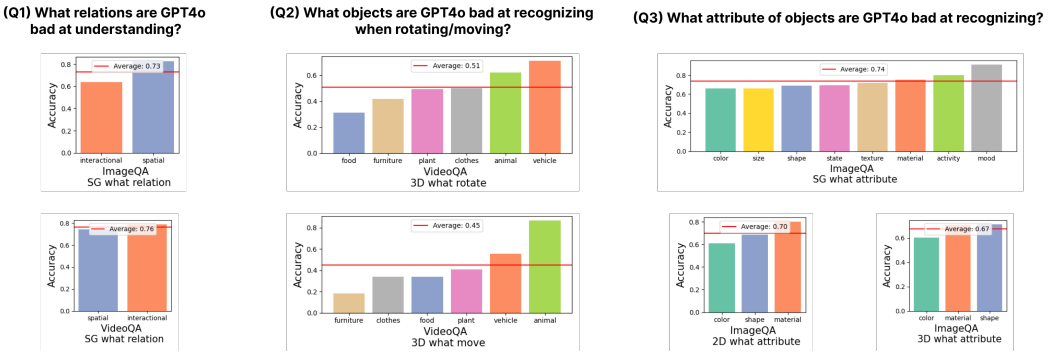


Figure 18: Answering Q1-Q3 with GPT4o performance on randomly generated task instances relating to coarse-grained object/relation/attribute categories.

Answering with individual objects/relations/attributes. To pinpoint the specific objects/relations/attributes that GPT4o can't do well, we convert each question to a Top-K query regarding individual objects/relations/attributes, and employ our *Active* method for query results approximation with a budget of GPT4o calls. We found that GPT4o's performance drops by a large margin (-5% to -50%) on the Top-5 objects/relations/attributes founded by TASK-ME-ANYTHING, indicating they remain challenging for GPT4o (Table 2). This example use case of TASK-ME-ANYTHING demonstrates how to leverage the system for locating the model weakness regarding fine-grained concepts.

Table 2: Answering Q1-Q3 with Top-K query regarding individual objects/relations/attributes. We also present the GPT4o performance drop (Δ Perf. (%)) on task instances involving found task elements as ground truth answers compared to random task instances, and show that performance drops by a large margin.

Question	Task generator	Top-K objects/relations/attributes	Δ Perf. (%)
what objects are GPT4o bad at recognizing when rotating/moving?	VideoQA 3D what rotate	*fermentation product, hamper, tool, computer keyboard, mathematical instrument*	-21.67
	VideoQA 3D what move	*towel, bathtub, furniture, air conditioner, desk*	-19.33
what relations are GPT4o bad at understanding?	ImageQA SG what relation	*taller than, exiting, pushing, pushed by, between*	-51.05
	VideoQA SG what relation	*beneath, covered by, carrying, above, standing on*	-16.66
what attributes are GPT4o bad at recognizing?	ImageQA 2D what attribute	*purple, brown, red, gray, beige*	-5.33
	ImageQA 3D what attribute	*stone, rubber, textile, leather, plastic*	-10.67
	ImageQA SG what attribute	*crooked, power, lower, steep, glowing*	-45.45

6 Related Work

We situate our work amongst existing work on large multimodal language models, programmatic task generation, and model-adaptive testing and debugging.

Large multimodal language models (MLMs). In recent years, large multimodal language models, by integrating visual encoders within various pretrained large languages models [94, 36, 11, 95, 83, 64, 86, 92, 56, 8, 12, 59, 75, 13, 80, 56, 63, 50, 85, 70, 5, 84], have progressively driven advancements in visual-language learning. With ubiquitous open-sourced LLM backbones and the increasing data for visual instruction tuning. Models like InstructBlip [18], QwenVL [6], LLaVA [58], InternVL [14], etc, have achieved unprecedented visual understanding performance in nearly all kind of visual tasks. Not only for static images, in the filed of video, by adding temporal information into the training and fine-tuning process. Models like VideoLLaMA [100], VideoChatGPT [65], ChatUnivi [42], VideoLLaVA [55], and VideoChat2 [53] have extended their capabilities to encompass video. These models, take both visual content and language as input and output language, are being considered as a new type of foundation model. The rise of large multimodal models has catalyzed the evolution of multimodal benchmarks [22, 93, 99, 49, 101, 78, 38, 66, 102, 87, 23, 9, 103, 17, 37, 27, 57, 71, 61], making them both broader and deeper. On the breadth axis, works such as MMBench[60], SEED-Bench [52, 51] and MMMU [97] provide comprehensive and integrated VQA benchmarks to evaluate a model's performance overally. On the depth axis, efforts like MathVista [62], Blink [24], MultipanelVQA [21], and Lance [77] focus on specific areas of visual tasks, such as spatial

reasoning, multipanel images understanding, counterfactual images understanding, etc. To evaluate the models' ability in specific domains or tasks.

Programmatic task generation. Leveraging program to generate scalable and controllable benchmark data to evaluate models has been explored in various tasks, Within the task of VQA. Early attempts like the CLEVR [43] dataset, which generates simple 3D shapes to test models' visual reasoning, GQA dataset[39], using programs to generate questions from real images have achieved great success. The advent of vision models has given them the ability to tackle more complicated and compositional vision tasks, and the need for comprehensive and complex programmatic benchmarks has emerged. SimVQA[10], integrated 3D models and simulated 3D environments, to generate photo-realistic, multi-physics synthetic scenarios with questions. Moreover, leveraging the advantages of programmatic benchmark generation, such as those used in 3DB [48], allows for precise targeting and identification of subgroups where models underperform.

Model-adaptive testing and debugging. In the past decades, we used the static "training set, test set" paradigm to evaluate the model's performance. However, as the foundation models are all trained on a wide spectrum of datasets, this paradigm might face overfitting and data contamination issues, which makes it hard to evaluate the performance of a model fairly and truly. Model-adaptive testing and debugging, consequently, emerges to solve this problem. The key idea is 1): dynamically update the test data to prevent overfitting and data contamination. Dynabench [46], for instance, uses human and model collaboration to create challenging benchmarks. Additionally, LatestEval [54] uses the latest texts to evaluate the model, avoiding training data overlap, and [96] automates dataset updates through stylistically similar samples generated by LLMs. 2): adaptively identify subgroups where models underperform and adjust task ratios accordingly. AdaVision [26], an interactive tool for iterative testing and refinement of computer vision models, pinpoints and addresses their systematic failures with user involvement. Moreover, [88]'s 3S Testing employs synthetic data to focus evaluations on minority subgroups and distributional shifts. Lifelong Benchmarks [76] proposes dynamically expanding benchmarks and an innovative algorithm to handle the increasing data and evaluation demands efficiently.

7 Conclusion

In this work, we introduce TASK-ME-ANYTHING, a task generation and evaluation system designed to address user queries with different evaluation objectives. We conduct various analyses and case studies based on TASK-ME-ANYTHING and existing MLMs, and offer many insights to the headroom for future model improvements. There are some limitations in this first version of TASK-ME-ANYTHING. For example, the current task space is more about models' perceptual capabilities and don't test for complex reasoning capabilities, which we plan to address in future versions by adding more task generators into TASK-ME-ANYTHING.

Contents

A Discussion

A.1 Limitation

Programmatically generated tasks can be unrealistic and biased. Programmatically generated tasks can lack the complexity and variability found in real-world data. These tasks might not capture the nuances of real-world scenarios, leading to models that perform well on synthetic data but fail in practical applications. The constraints and rules defined in the code may oversimplify the tasks, making them easier for models to solve compared to real-world tasks. This can result in overestimating a model's capabilities. The rules and logic used to generate tasks can inadvertently introduce biases. For example, if the code disproportionately generates certain types of objects or scenarios, the model may not be adequately tested on a diverse range of tasks.

Designing the task space is challenging. Identifying and defining the relevant attributes for each task type (e.g., object recognition) requires deep domain knowledge and understanding of what aspects are critical for evaluating model performance. The task space must be comprehensive enough to cover various scenarios but not so complex that it becomes infeasible to manage or evaluate. Striking this balance is a significant challenge. The task space should be designed to ensure comprehensive coverage of all relevant scenarios and diversity in the types of tasks. This requires meticulous planning and consideration of all possible task variations.

Adding new task generators requires coding skills. Adding new task generators involves programming and understanding the underlying framework used for task generation. This requires technical expertise, which may not be available for all communities and can be a barrier for non-technical researchers who might have valuable insights and ideas for new tasks but lack the coding ability to implement them.

Query results approximation can be inaccurate. Efficient query results approximation within certain budgets might sometimes yield inaccurate results, especially when the budget limits are constrained. This inaccuracy can stem from several factors. First, the models that embed tasks into vectors may not fully capture all the details and nuances between different tasks. Second, the algorithms used for querying might have inherent limitations or room for improvement, affecting the precision of the results. Addressing these issues requires ongoing refinement of both the task embedding models and the query algorithms to enhance their ability to deliver accurate approximations under varying computational budgets.

A.2 Potential negative social impact

Misuse for malicious benchmarks. TASK-ME-ANYTHING's ability to generate a vast number of tasks could be misused to create benchmarks specifically designed to trick or expose vulnerabilities in AI systems. Malicious actors might use this capability to create benchmarks that mislead researchers or lead to the development of AI models with undesirable biases or vulnerabilities.

Reinforcement of biases and discrimination. If TASK-ME-ANYTHING's task generators are not carefully designed and curated, they could inadvertently perpetuate existing biases present in the source data. This could lead to the development of AI models that are biased against certain groups of people or perpetuate harmful stereotypes.

Overreliance on synthetic tasks. The focus on synthetic task generation could lead to a disconnect between evaluation results and real-world performance. Overreliance on synthetic tasks might create a false sense of progress and hinder the development of AI models that can effectively address real-world challenges.

Data contamination. Fine-tuning models on synthetic tasks generated by TASK-ME-ANYTHING could lead to data contamination, where the model learns to exploit the specific patterns and biases of the synthetic data rather than generalizing to real-world scenarios. This could result in models that perform well on synthetic benchmarks but poorly in practical applications.

Access and fairness. While TASK-ME-ANYTHING aims to democratize AI evaluation, the technical expertise required to implement new task generators could create barriers for researchers and practitioners from underrepresented groups, leading to a lack of diverse perspectives and potentially reinforcing existing inequalities.

A.3 Future work

Supporting natural language user queries. We plan to enable natural language queries, allowing users to specify evaluation needs in plain language. This will leverage language models to translate instructions into actionable query commands, making the system more accessible and user-friendly. This enhancement will democratize access to model evaluation, streamline the process, and reduce barriers for non-technical users, fostering a more inclusive evaluation ecosystem.

Expanding the TASK-ME-ANYTHING system. To further enhance the capabilities of TASK-ME-ANYTHING, we plan to extend it across a broader range of scenarios and model types. This involves integrating support for various generative models, including language models and visual generative models, which can fine-tune the evaluation of generation quality. Also, by incorporating new types of source data, we aim to enrich the diversity and relevance of the tasks generated, ensuring that the evaluation framework remains robust and comprehensive as foundation model capabilities advance. Additionally, developing new task generators will enable the creation of tasks that capture emerging AI challenges and applications, facilitating continuous adaptation to the evolving landscape of AI. This expansion will empower users from different domains to evaluate models in ways that are highly specific to their needs, ultimately contributing to more targeted and effective deployment of AI technologies.

A new workload for database study. TASK-ME-ANYTHING presents new opportunities for the database community to develop efficient query execution techniques on conceptual relations containing model inference results (e.g., task accuracy of many models on many tasks) that are expensive to compute and often unmaterialized when a query is issued. The idea of pre-filtering to avoid expensive computation has been proven to be effective in some database problems, such as accelerating similarity joins [67, 41] and video analytics queries [44] where computing the similarity function or running model inference on videos is expensive during query execution. In a similar vein, recent work [34, 33, 90] has proposed efficient database indexing and query execution techniques to navigate the tradeoffs between storing the model inference results on disk and computing them on-the-fly at query time. Some other efforts [3] have also proposed trading off query result accuracy for query response time. Another direction for future work is query result diversification. When a practitioner explores a set of MLMs, datasets, and tasks, they may desire to examine a diverse set of result items, e.g., tasks that are dissimilar. It would be interesting to how query result diversification techniques [28, 35] could be adapted in TASK-ME-ANYTHING's setting.

B Details of Task Generation

In this section, we describe the details of the programmatic task generation process in TASK-ME-ANYTHING. We focus on tasks of multiple-choice visual questions answering, including both image question answering (ImageQA) and video question answering (VideoQA).

B.1 Key concepts

First, we introduce several key concepts and definitions in our task generation process.

Task instance, task, and task plan. A task instance is an image/video, question, options, and ground truth answer tuple that comprises a single evaluation test-case. A task is a conceptual abstraction consisting of all task instances that share the same question and answer. Tasks are specified via task plans, which contain the required task metadata and configurations to create the actual task instances. For example, in tasks involving counting, the task plan specifies the categories of objects, their total numbers in the scene, and their positions in the image—such as two apples, one on the top right and one on the bottom left. The task instance then features an actual image of the target objects and includes a specific question and answer that is consistent with the arrangement of these objects in the scene. One such task instance might be an image with two apples, the question: "How many apples are there in the image?", and the answer: "2". Multiple task instances can be generated from a single task plan because other elements such as the image background and types of distractor objects can be randomized, as they are not specified in the task plan.

Source data. We refer to source data as the visual data and annotations that are used to generate task instances, *e.g.*, the 3D objects from Objaverse [20, 19] and their associated annotations or the real images and scene graphs from GQA [39, 47].

Task generator. Each task generator is a program that, given source data as input, generates task instances of a certain type. It achieves three main purposes: 1) it defines the schema of the task plan; 2) it can enumerate all possible task plans given the available source data; and 3) given source data and a specific task plan, it can randomly generate a task instance belonging to the task family defined by the task plan.

B.2 The generation process

Given the source data and a task generator, one can readily generate a large number of tasks. The overall generation process consists of the following steps:

Step 1: enumerate the task plans. Once the task generator is implemented, one can use it to enumerate and return all the possible task plans based on the defined schema and the source data. As each task plan consists of just the metadata of the task rather than the actual task instances, it is efficient to enumerate all the task plans and store them as a single table. Note that enumerating all possible task plans is a one-time job, since the table of task plans can be stored and reused.

Step 2: generate task instances of a task given its task plan. Another core functionality of the task generator is to generate one task instance given a valid task plan. Note that the task generator may generate many different task instances because of the randomness, *e.g.*, the negative choices can be randomly sampled from possible candidates, yet since they are all generated by the same task generator with the same task plan, they would share the question and ground truth answer and are considered belonging to the same task.

Properties. This task generation process exhibits several key properties:

- **Reproducible:** With our task generation process, the tasks are produced as a combination of the source data and the programs, therefore one can reproduce identical task instances with the same source data and the random seed of the program.
- **Scalable:** This task generation process is scalable for two reasons. First, it is *memory-friendly*. One only needs to store the source data and the annotations, as well as our

codebase. Even when one aims to evaluate a model on millions of task instances, since the task instances are reproducible, one can choose to generate the task instances on the fly rather than beforehand. Secondly, it is *easy to expand* the space of task that can be generated. One can increase the number of possible tasks by either adding new source data or new task generators.

- **Easy to update:** Benchmarks can contain unexpected errors, *e.g.*, annotation error [72], so the task generation process must be easy to update once the error is caught. Since our task generation process is transparent to the users, once an error is caught, it can immediately be attributed to either the error of the source data or bugs in the code of the task generators, and then be fixed. We welcome the whole community to report any flaw in our task generation process.
- **Structured task space:** Finally, each task generated by our approach is associated with a task plan composed of its metadata. This design offers a natural structure for the tasks so that they can be grouped by certain specifications of task metadata. It enables users to navigate wanted tasks by querying the table of task plans as querying a normal database. Also, it facilitates the diagnosis of models according to the task metadata.

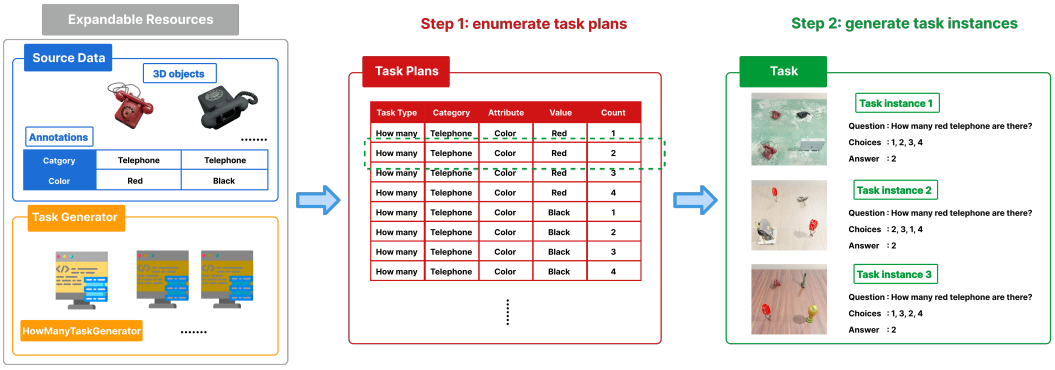


Figure 19: An illustration of core concepts and the task generation process.

C Details of Fine-grained User Query and Query Approximation Algorithms

With TASK-ME-ANYTHING, most user queries regarding model performance can be simply addressed by identifying the relevant task generators and a subset of the task plans to generate task instances for model investigation. However, there is a special family of fine-grained user queries regarding individual tasks and taxonomy concepts that may require a large number of tasks to be appropriately addressed. For example, *the colors that the minimum performance of models M1, M2 is larger than 50%*; such a query involves tasks related to all the color attributes and concerns the models' performance on each individual color. In this section, we outline four types of such fine-grained user queries and discuss how to address them with efficient query results approximation.

C.1 Fine-grained user query

We introduce four types of fine-grained user query. By default, the target of a query is the tasks, *e.g.*, Top K <task>; one can also query different task metadata or their products, *e.g.*, Top K <category> or Top K <category $\times$ attribute>.

Top-K query. Users may be interested in knowing the tasks or task metadata (*e.g.*, object category) that the model(s) performs the best or the worst, which can be supported by a Top-K query. An example Top-K query in natural language is, *(E1) Top 10 "how many" tasks ranked by the maximum performance of the user-specified list of models (the user specifies all models in this case) in descending order*. This query finds the top 10 tasks that all models perform the best, measured by the maximum performance of the models on each task.

Threshold query. Another useful type of query is the Threshold query, since users may want to know the tasks or task metadata on which the model's performance is larger or lower than a given threshold. An example in natural language is, *(E2) The color attributes on which the mean of the minimum performance of models M1, M2 is larger than 50%*. The query first groups tasks by their color value attribute and then aims to find the groups where the mean of the minimum performance of M1 and M2 across all tasks in the group is larger than 50%.

Built upon basic queries, one can develop new types of queries to fulfill specific needs, *e.g.*, comparing models or diagnosing the model. Here, we showcase two advanced queries based on the Threshold query: model compare and debug.

Model Comparison query. A useful type of query is to support comparing a model to another. In contrast to the traditional way of comparing models by ranking based on their performance, our *Model Comparison Query* supports finding tasks or patterns where one model performs better than the other by a given threshold. An example query is *(E3) The task types on which the mean performance of model M1 is larger than model M2*.

Model Debugging query. Model debugging is an important field of study for model evaluation [**?**], where the goal is to find patterns or subgroups where the model performs significantly worse or better than its average performance. To fulfill this need, we support *Model Debugging Queries* by leveraging the Threshold query with the threshold being a function of the model's average performance and a hyperparameter. For example, to find tasks where the model performs significantly worse than average, we can use the Threshold query and set the threshold to be $\mu - \sigma$, where μ is the averaged performance of the model and σ is the standard deviation of the model performance. An example query is *(E4) The tasks on which the performance of model M1 is lower than its average performance of all tasks by a standard deviation*.

Note that these two types of query can be similarly defined based on the Top-K query, *e.g.*, the Model Debugging query can be the top k tasks that a model performs the worst, and how to define these queries depends on the user need.

C.2 Query execution

We provide an example of the conceptual query execution process in Figure 20, which illustrates the steps required to execute query E2. Query E2 requires these steps:

1. Filter: the query filters the task plans related to "color".
2. Generate and evaluate: the query needs to generate the tasks given the obtained task plans and then evaluate model M1 and M2 against these tasks to collect their accuracy for each task.
3. Aggregate: once we obtain models' accuracy on every involved task, we perform some aggregate functions to collect the final results. We first compute the minimum accuracy of models M1 and M2 on each task. Then we average the obtained minimum accuracy over tasks within one color value group, to gather the final results for each color value group.
4. Select: for each group, the query checks whether the final result is greater than 0.5 and only keeps the groups where this filter condition holds.

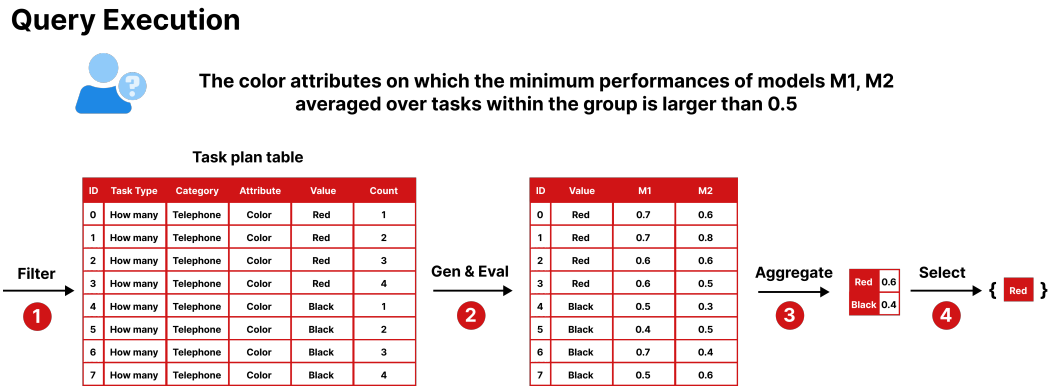


Figure 20: An illustration of the query execution process.

Incorporating frequent pattern mining. In practice, users may be more interested in knowing the patterns revealed by the returned tasks than the tasks themselves. Because each task in our system is associated with a task plan, one can apply frequent pattern mining [32, 91, 31] to extract frequent patterns from the set of task plans associated with the returned tasks. Note that frequent pattern mining can be applied to the results of any type of query as long as there is a set of associated task plans.

C.3 Efficient Query Approximation Algorithms

As the fine-grained user queries may involve a large number of tasks to evaluate and therefore likely become computationally infeasible due to the compute-intensive nature of MLMs, we study three algorithms to approximate the query results given a budget of B on the number of tasks to be evaluated.

Subset proxy. One straightforward approach to approximate the query results is to spend the budget randomly sampling B tasks and then evaluate the models against them to obtain the results. Then, we use this sampled subset as a proxy of the whole set of tasks to perform the fine-grained user query.

Fitting. Built upon the subset proxy method, the fitting method uses the evaluation results of the B randomly sampled tasks to train a model (referred to as *function approximator*) to approximate the function of interest, and then apply the model to the rest of the tasks to predict the results. In particular, the function of interest can be the model's accuracy function which inputs a task and predicts the model's accuracy, or the task aggregate function, *e.g.*, the minimum accuracy of two models as in query E2. Finally, we perform the query over all the tasks, with both actual evaluation results on B sampled tasks and values of the remaining predicted by the function approximator.

Active evaluation. The third approach, active evaluation, builds upon the fitting method but enhances it by strategically selecting tasks to improve the approximation of query results, as opposed to relying on random sampling. This method utilizes an iterative process, where each step involves selecting a batch of unevaluated tasks based on predictions made by the current function approximator.

These tasks are then evaluated, and the results are used to re-fit the function approximator with both existing and new data until the evaluation budget is exhausted. Ultimately, the query is executed using a combination of actual results from evaluated tasks and predicted results, similar to the fitting method. The task selection criteria are tailored to the specific type of query. For the Top-K query, it selects the top-K tasks most likely to fulfill the user's inquiry based on the predicted values, because these tasks are predicted to have the most significant impact on the outcome of the query, and focusing on them could help learn a function approximator with more accurate predictions in areas that are likely relevant to the actual query results. For the Threshold query, it selects the tasks whose predicted values are closest to the threshold, because these tasks are most likely to influence the decision boundary of the function approximator and thus are critical for accurately determining the boundary's position within the task space.

Implementation details. To learn a function approximator to predict the value of interest, we first need a representation of each task as the input of the approximator. We construct such representation using the task plan, question, and answer associated with each task. In particular, we convert these elements into a piece of formulated text and leverage pre-trained embedding models to calculate the text embedding as the task embedding. We adopt Gaussian Process regressor[3] because of its stable performance in our preliminary experiments, while any regression model is applicable.

[3] https://scikit-learn.org/stable/modules/generated/sklearn.gaussian_process.GaussianProcessRegressor.html

D Details of TASK-ME-ANYTHING 1.0

In this section, we introduce the task generators implemented in the first version of TASK-ME-ANYTHING. Inspired by the model cards for model reporting [69], we make a task generator card for each implemented task generator, including information such as task type, task plan schema, *etc.*, available in the appendix, and the template can be found in Figure 21.

Task Generator Card Template

- **Basic Information**.
  - **Task Type**. The target type of task, *e.g.*, ImageQA
  - **Question Type**. The type of generated question, *e.g.*, "how many"
  - **Answer Type**. The answer type *e.g.*, integer number or object category
  - **The model capability to evaluate**. *e.g.*, counting
- **Source Data**. The source data and annotations it requires
- **Task Plan Schema**. The schema of the associated task plans
- **Partitions**. The partition of the task space.
  - **Partition 1**.
    - **Template**. Template used to generate question if available
    - **Example**. An example of generated test case
- **Limitations**
- **Recommendations**

Figure 21: Summary of task generator card sections and suggested prompts for each. Task generator cards for all the included task generators can be found in Appendix I.

D.1 Source data

3D objects with annotations. We start by selecting objects from Objaverse-LVIS, the subset of Objaverse 1.0 [20] that has been annotated with LVIS [30] categories. From the set of 47K objects spanning 1,230 categories that comprise Objaverse-LVIS, we select 1,996 objects spanning 337 categories. These objects were manually chosen for their high quality and strong category alignment. We use Blender [15], an open-source ray-tracing software, to render each object from a uniform set of surrounding viewpoints and, following manual verification, only keep renderings where the object's category and attributes are discernible. This gives us a set of viewpoint annotations that we also use when constructing 3D scenes, as they allow us to ensure that the object's category and attributes are perceivable from the camera.

Real images and videos with *Scene Graph*. We also collect real images and videos with scene graph [47] as part of our source data. In particular, we collect real images with scene graphs from the GQA dataset [47, 39] and real videos with scene graphs from the AGQA dataset [40, 81].

Additionally, we normalized the object terms across all source data and built a taxonomy containing 927 concepts and 965 edges using Wikidata and human filtering to avoid concept conflicts in options, such as listing both "apple" and "fruit" as choices.

D.2 Task generators for different scenarios

D.2.1 2D sticker image

The first scenario of TASK-ME-ANYTHING is *2D sticker image*, where we compose task instance images by compositing pre-rendered object images into a 2x2 or 3x3 grid. Such a simple type of image already enables the generation of basic types of visual questions regarding recognizing object categories and attributes, spatial relations, and counting. For example, one task could be *how many*

red telephones are there in the image?. We list the task generators implemented for *2D sticker image* and the statistics in Table 3.

Table 3: *2D sticker image*

Task generator	Example question	Example answer	# of tasks
how many	How many blue objects are there in the image?	2	494
	How many tables are there in the image?	4	6,136
	How many pink beverages are there in the image?	2	27,027
what	What is the object in the bottom middle part of the image?	folding chair	33,163
	What is the object to the left of the telephone?	table lamp	61,648,184
where	Where is the apple in the image?	back left	33,163
	Where is the vacuum cleaner with respect to the backpack?	left	61,648,184
what attribute	What is the material of the object in the middle part of the image?	plastic	27,027
	What is the color of the object to the left of the silverware?	gold	50,175,008
where attribute	Where is the white object in the image?	top right	27,027
	Where is the gray object with respect to the lollipop?	top	50,175,008
Total number of tasks: 223,800,421			

D.2.2 3D tabletop scene

Although *2D sticker image* is a useful setting for generating task instances with speed, the artificial way in which the scenes are constructed through image compositing limits their realism. A real-world scene would come from objects existing in a shared 3D space that is rendered through the perspective of a single camera. As such, in *2D sticker image* we are unable to understand the effects of depth, lighting and occlusion on image understanding. To remedy this, we introduce *3D tabletop scene*, a setting analogous to *2D sticker image*, wherein objects are arranged on a plane in a shared 3D scene and rendered from a fixed camera viewpoint. This allows us to port all of the task generators from *2D sticker image* while also allowing us to test 3D-specific capabilities such as relative depth.

ImageQA. Another way to generate similar yet more realistic images is to compose a 3D tabletop scene using the objects, and then render a 2D image [43]. For this *3D tabletop scene*, we can reuse task generators of *2D sticker image* with some minor modifications regarding the spatial relations. For example, the spatial relation of "in the bottom of" would become "in front of". In addition, we identify two families of task generators unique to 3D scenes: tasks regarding the size and distance of objects, which are not suitable for the 2D scenario discussed above. We list the task generators implemented for ImageQA of *3D tabletop scene* and the statistics in Table 4.

VideoQA. In addition to the aforementioned ImageQA tasks, we also build VideoQA tasks for *3D tabletop scene*. We leverage two temporal attributes, rotation and movement, which can only be identified via video, to construct video-specific task generators and evaluate the models' performance in understanding temporal dynamics. To generate these videos, we keep the same layout of the 3D tabletop scene as ImageQA, but change the positions and angles of the objects across different frames of the video to make the objects move and rotate. Our task generators then target the model's ability to understand these temporal changes in object position and orientation. We list the task generators implemented for VideoQA of *3D tabletop scene* and the statistics in Table 5.

D.2.3 Real images/videos with scene graphs

We also leverage existing manually-annotated scene graph data, *i.e.*, GQA and AGQA, to construct task generators. For ImageQA, because there are three types of nodes in the scene graph for images, *i.e.*, object, relation, and attribute, we accordingly implement three task generators to evaluate models' capability in recognizing these basic visual elements. Similarly, the scene graph for videos consists of three types of nodes, *i.e.*, object, relation, and action, we implement three task generators regarding these visual elements. We list the task generators implemented for ImageQA and VideoQA leveraging scene graphs and the statistics in Table 6&7.

Table 4: *3D tabletop scene* with images

Task generator	Example question	Example answer	# of tasks
how many	How many blue objects are there in the image?	6	494
	How many plates are there in the image?	5	6,136
	How many black furnitures are there in the image?	4	27,027
what	What is the object in the front right part of the image?	scale	33,163
	What is the object to the right of the mobile computer?	bucket	61,648,184
where	Where is the vacuum cleaner in the image?	back left	33,163
	Where is the vacuum cleaner with respect to the wine glass?	left	61,648,184
what attribute	What is the color of the object in the back left part of the image?	red	27,027
	What is the material of the object behind the plate?	wood	50,175,008
where attribute	Where is the wood object in the image?	front right	27,027
	Where is the white object with respect to the trophy?	left	50,175,008
what size	What is the smallest object in the image?	spatula	20,408
what attribute size	What is the color of the smallest object in the image?	black	16,632
where size	Where is the largest object in the image?	back left	20,408
	Where is the smallest object in the image with respect to the car?	front	56,906,016
what distance	What is the object that is farthest from the optical instrument?	juice	61,648,184
what attribute distance	What is the color of the object that is closest to the statue?	beige	50,175,008
where distance	Where is the object that is farthest from the bread in the image?	middle	61,648,184
Total number of tasks: 454,235,261			

Table 5: *3D tabletop scene* with videos

Task generator	Example question	Example answer	# of tasks
what rotate video	What is the object that is rotating counterclockwise in the video?	pants	20,408
	What is the rotating object in the video?	jewelry	20,408
what attribute rotate video	What is the color of the object that is rotating clockwise in the video?	beige	16,632
	What is the color of the rotating object in the video?	yellow	16,632
where rotate video	Where is the stepladder with respect to the rotating object in the video?	back	51,631,112
	Where is the object that is rotating counterclockwise with respect to the microscope in the video?	front left	62,221,736
what move video	What is the object that is moving left in the video?	serving tray	40,816
	What is the moving object in the video?	barrel	40,816
what attribute move video	What is the color of the object that is moving left in the video?	black	33,264
	What is the color of the moving object in the video?	white	33,264
where move video	Where is the object that is moving down located in the video?	back right	40,816
	Where is the moving object located in the video?	back right	40,816
Total number of tasks: 114,176,720			

Table 6: Real images with *Scene Graph*

Task generator	Example question	Example answer	# of tasks
what object	What is the flat object that is on the brown and wood table?	paper	25,169
what attribute	What is the material of the smooth object that is to the right of the yellow container?	plastic	20,554
what relation	What is the relation from the standing object, which the colorful and long snowboard is to the right of, to the blue and long object, which is to the left of the patterned skis?	holding	23,241
Total number of tasks: 68,964			

Table 7: Real videos with *Scene Graph*.

Task generator	Example question	Example answer	# of tasks
what object video	What is the spatial relation of the person to the closet while the person closing a closet?	floor	428,342
what relation video	What is the object that the person is behind after the person watching something in a mirror?	behind	211,983
	What is the person doing to the blanket before the person putting a phone somewhere?	touching	216,359
what action video	What action is the person doing while laughing at something?	sitting at a table	335,386
Total number of tasks: 1,192,070			

D.3 TASK-ME-ANYTHING-UI

The ultimate goal of our query-centric model evaluation framework is to allow diverse users, including ML practitioners and non-technical users, to understand foundation models' capabilities and

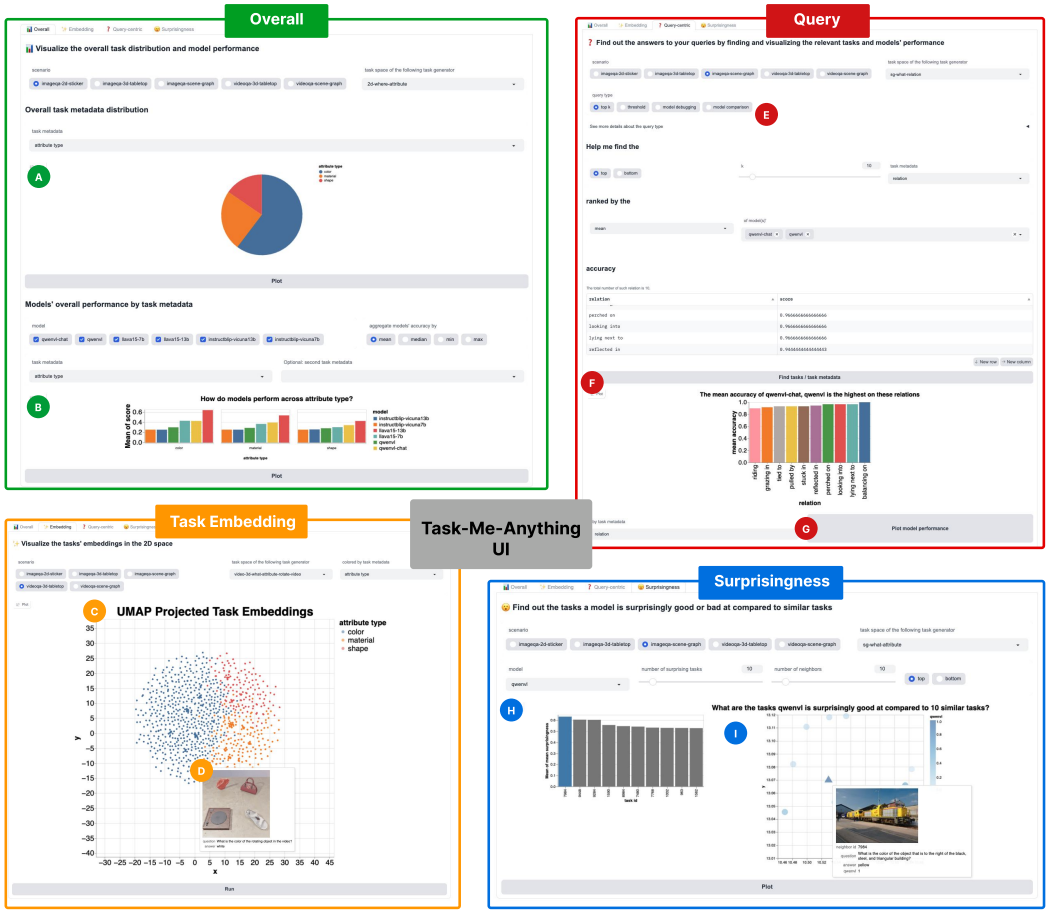


Figure 22: TASK-ME-ANYTHING-UI Interface.

limitations comprehensively and dynamically by answering their various case-specific queries. To achieve this overarching goal, we further break it down into three subgoals and aim to design an interactive end-user interface to achieve these goals:

G1: Support understanding of the overall task space and model performance;

G2: Enable deeper understanding of models through query-centric visualization of model performance (especially for common queries);

G3: Facilitate model debugging via discovery of surprising results.

To achieve these goals, we implemented a graphical user interface[4] with Gradio's [1] framework and used Altair [89, 79] for all the visualizations. In this section, we describe our interface in detail and how its components aim to address our design goals. Then, we present several case studies using this interface in the next section. Our interface consists of four major components organized as different tabs:

Overall. As the name suggests, the Overall tab is designed to help users understand the overall task distribution and model performance (**G1**). It consists of two horizontal sections for visualizing overall task distribution ((A)) and models' overall performance ((B)) respectively. Section A displays a pie chart of the distribution of all tasks by metadata based on user's choice of task metadata, while Section B visualizes certain models' aggregated performance in either a bar plot or heat map according to user-selected models, aggregation method and task metadata. We choose these common chart types in hopes of supporting straightfoward understanding of the overall task space and model performance.

[4] https://huggingface.co/spaces/zixianma/TaskMeAnything-UI

Task embedding. In addition to the overall task distribution, we also include the Task Embedding tab to allow users to visualize all tasks at once in a 2D embedding space (**G1**). Concretely, the Embedding tab plots the 2D embeddings of all tasks reduced by UMAP as dots in a scatter plot (C). Further, we add a descriptive tooltip for each dot that displays an example image or video along with the corresponding question-answer pair for this task (D). By visualizing all tasks in one plot and enabling detail of individual tasks on demand at the same time, we hope the interface can help users understand the entire task space well on both high and low levels.

Fine-grained user query. Most importantly, our interface supports query-centric visualizations of model performance under the Query-centric tab. While the space of possible user queries can be infinite, we define four common user queries: top k, threshold, model comparison and model debugging (Section 2.3) and support corresponding visualizations (E). As these queries involve selecting a subset of tasks for visualization, we include a "Find tasks/task metadata" button to first select the relevant tasks based on the user query and return these tasks in a table (F). If the user selects task metadata, they will have the option to visualize models' performance on the selected task metadata (G). If the user chooses to find individual tasks however, they can additionally visualize the task distribution by some metadata, or find frequent patterns among tasks. By specifying a query first and visualizing models' performance only on selected tasks/task metadata, users can gain a more targted understanding of models based on what they are interested in (**G1**). In particular, the model debugging query can help the user find buggy model behaviors by identifying tasks/task metadata where the model's performance is lower than its global average accuracy by a large margin i.e. one standard deviation (**G2**).

Surprisingness. Last but not least, we include the Surprisingness tab to help users uncover tasks where models achieve surprisingly good or bad performance compared to their performance on similar tasks (**G3**). We define the "surprisingness" of a model M on a particular task T_i as the following: For a task, T_i and its K nearest neighbors tasks $\{T'_j\}$, we compute the surprisingness score as

$$s_i^M = \frac{1}{K} \sum_{j=1}^{K} \left(\text{sim}(T_i, T'_j) \times (f(T_i, M) - f(T'_j, M)) \right) \tag{1}$$

A higher score indicates the model M is much better at task T_i than the neighbor tasks, while a lower score means M is worse at T_i than the neighbors.

Under the Surprisingness tab, we display the tasks where the model achieves the highest surprisingness scores in a bar chart (H). We also make the bar chart interactive so that the user can select a particular surprising task. Then, the scatter plot on the side visualizes this model's performance on the user-selected task accordingly along with the k most similar tasks in the 2D embedding space (I). With this interactive visualization of surprising tasks, we hope to allow users to uncover unexpected model behaviors quickly.

E Details of Model and Human Performance on Random Task Instances

In this section, we present the full results of our evaluation on TASK-ME-ANYTHING-RANDOM with 18 MLMs and human anntators.

E.1 Raw results of Figure 6

Table 8: **TASK-ME-ANYTHING-RANDOM-ImageQA**. The model performance on random subsets of ImageQA tasks using both the detailed prompt and the succinct prompt. Numbers in parentheses are the number of task instances for each set.

	2D sticker image (1,500)		*3D tabletop scene* (3,300)		*Scene Graph* (900)	
	Detailed prompt	**Succinct prompt**	**Detailed prompt**	**Succinct prompt**	**Detailed prompt**	**Succinct prompt**
Human	99.40		99.73		97.33	
INSTRUCTBLIP-7B	28.27	0.60	34.48	0.45	68.33	0.11
INSTRUCTBLIP-13B	28.34	23.87	33.12	24.73	65.22	66.11
QWEN-VL	33.40	13.33	33.48	15.91	68.78	12.56
QWEN-VL-CHAT	40.40	35.87	38.88	39.36	78.33	79.45
LLAVA-7B	37.93	41.87	37.55	39.24	62.00	75.22
LLAVA-13B	45.60	43.20	43.97	42.39	79.22	82.78
INTERNVL-CHAT-1.5-24B	58.60	57.40	61.06	59.64	84.67	82.33
LLAVA-NEXT-34B	62.80	62.33	56.33	58.06	85.66	84.89
GEMINI-PRO	30.60	31.47	33.03	31.09	56.78	60.89
QWEN-VL-MAX	55.46	53.33	53.49	55.06	85.67	89.33
GPT4V	34.60	52.40	36.73	47.55	73.44	71.78
GPT4O	45.33	54.80	46.00	58.61	76.33	77.34

Table 9: **TASK-ME-ANYTHING-RANDOM-VideoQA**. The model performance on random subsets of VideoQA tasks using both the detailed prompt and the succinct prompt. Numbers in parentheses are the number of task instances for each set.

	3D tabletop scene (1,800)		*Scene Graph* (900)	
	Detailed prompt	**Succinct prompt**	**Detailed prompt**	**Succinct prompt**
Human	98.33		99.33	
VIDEO-CHATGPT-7B	21.44	21.39	30.45	25.67
VIDEO-LLAVA-7B	26.00	38.78	32.11	56.67
VIDEOCHAT2-7B	30.61	28.55	37.89	32.89
VIDEO-LLAMA-2-7B	23.78	16.33	36.34	31.67
VIDEO-LLAMA-2-13B	22.67	20.23	30.78	28.45
CHAT-UNIVI-7B	29.72	25.95	50.11	45.00
CHAT-UNIVI-13B	28.17	25.67	45.22	39.89
INTERNVL-CHAT-1.5-24B	38.33	31.67	68.11	56.33
LLAVA-NEXT-34B	40.06	41.17	67.55	63.44
GEMINI-PRO	31.78	30.11	50.00	45.78
QWEN-VL-MAX	38.89	39.39	69.11	66.78
GPT4V	30.95	36.83	59.11	62.67
GPT4O	35.67	41.72	69.56	66.22

E.2 A breakdown of Table 8

Table 10: *2D sticker image*

	how many		what		what attribute		where		where attribute	
	DP	SP	DP	SP	DP	SP	DP	SP	DP	SP
Human	100.00		98.00		100.00		100.00		99.00	
InstructBLIP-7B	23.67	0.00	24.33	0.00	39.67	0.00	27.00	1.00	26.67	2.00
InstructBLIP-13B	26.67	30.67	23.67	24.33	41.67	40.67	23.67	22.00	26.00	1.67
Qwen-VL	30.67	9.00	36.67	9.00	47.00	17.67	27.33	15.00	25.33	16.00
Qwen-VL-Chat	39.67	24.67	42.67	42.67	54.67	52.00	31.67	33.00	33.33	27.00
LLaVA-7B	42.00	40.67	40.00	45.67	48.67	49.67	31.00	39.00	28.00	34.33
LLaVA-13B	49.33	48.33	46.00	46.67	58.33	55.33	39.67	32.67	34.67	33.00
InternVL-Chat-1.5-24B	57.67	60.67	62.00	55.00	**75.33**	**72.33**	**51.33**	49.33	46.67	**49.67**
LLaVA-Next-34B	**68.33**	**64.67**	**63.33**	**62.67**	**72.00**	70.67	**57.33**	**58.33**	**53.00**	**55.33**
Gemini-Pro	33.33	34.33	32.67	38.00	32.33	33.00	26.67	28.33	28.00	23.67
Qwen-VL-Max	58.33	45.00	57.00	59.67	71.33	68.33	48.33	47.33	42.33	46.33
GPT4V	40.00	**68.67**	40.67	50.33	41.00	60.33	25.67	42.67	25.67	40.00
GPT4o	44.67	53.67	50.33	**62.33**	60.00	67.00	36.00	45.67	35.67	45.33

Table 11: *3D tabletop scene* part 1

	how many		what		what attribute		where		where attribute	
	DP	SP	DP	SP	DP	SP	DP	SP	DP	SP
Human	99.00		100.00		100.00		99.00		100.00	
InstructBLIP-7B	32.67	0.00	28.00	0.00	45.00	0.00	25.67	1.00	27.00	2.33
InstructBLIP-13B	32.00	32.33	22.67	23.33	42.67	0.00	28.67	25.33	23.00	24.67
Qwen-VL	32.33	11.00	28.00	8.67	50.67	19.67	22.67	18.33	24.67	15.00
Qwen-VL-Chat	45.00	33.33	32.33	33.33	55.00	57.00	21.67	24.00	29.67	32.33
LLaVA-7B	38.67	39.33	32.67	40.33	57.00	54.00	27.00	27.67	26.00	26.00
LLaVA-13B	46.67	48.33	40.67	41.00	60.33	56.00	34.33	32.67	36.00	32.67
InternVL-Chat-1.5-24B	**67.00**	**67.00**	**60.33**	**56.33**	68.33	65.67	**54.67**	**55.67**	**46.67**	**46.00**
LLaVA-Next-34B	63.67	63.33	49.67	50.67	**71.33**	**71.33**	48.33	**51.00**	40.33	**49.00**
Gemini-Pro	40.00	38.67	32.67	25.00	31.33	34.67	28.00	31.00	27.67	28.00
Qwen-VL-Max	65.00	60.67	54.67	55.33	63.67	61.33	42.33	44.00	32.67	37.33
GPT4V	41.67	**66.67**	31.67	37.67	41.33	54.67	25.00	39.00	25.67	28.33
GPT4o	45.00	64.33	47.33	**58.67**	57.33	**68.67**	37.67	45.33	30.67	44.33

Table 12: *3D tabletop scene* part 2

	what distance		where distance		what attribute distance		what size		where size		what attribute size	
	DP	SP	DP	SP	DP	SP	DP	SP	DP	SP	DP	SP
Human	100.00		99.00		100.00		100.00		100.00		100.00	
InstructBLIP-7B	17.67	0.00	38.33	0.00	51.00	0.00	30.33	0.00	32.33	1.67	51.33	0.00
InstructBLIP-13B	23.67	24.33	29.33	29.00	48.00	1.67	35.67	37.00	25.33	24.00	53.33	50.33
Qwen-VL	25.33	8.67	26.33	14.00	50.33	19.67	34.67	14.00	21.33	19.00	52.00	27.00
Qwen-VL-Chat	25.00	24.00	25.67	28.33	56.67	56.00	43.00	48.67	31.00	30.67	62.67	65.33
LLaVA-7B	28.00	30.67	26.33	25.67	49.67	48.67	43.00	44.67	29.33	34.67	55.33	60.00
LLaVA-13B	33.67	29.33	26.00	23.67	57.67	55.33	48.33	48.33	34.67	35.67	65.33	63.33
InternVL-Chat-1.5-24B	**52.33**	36.00	39.00	**47.00**	**69.67**	68.67	**73.33**	**73.67**	**57.67**	**57.67**	**82.67**	**82.33**
LLaVA-Next-34B	48.00	45.33	34.33	**40.67**	**75.00**	**74.00**	62.33	62.00	49.00	**52.67**	77.67	**78.67**
Gemini-Pro	39.33	31.00	25.33	24.33	38.33	36.00	34.33	29.67	26.67	26.67	39.67	37.00
Qwen-VL-Max	39.00	**53.00**	2.67	35.67	65.00	66.67	72.33	69.67	45.33	50.00	75.67	72.00
GPT4V	39.33	46.67	21.67	19.00	43.33	64.33	46.00	54.00	22.33	37.67	66.00	75.00
GPT4o	44.67	**62.33**	24.00	**41.67**	58.33	65.33	57.67	**73.00**	32.33	44.67	71.00	76.33

Table 13: Real images with *Scene Graph*

	what attribute		what object		what relation	
	DP	**SP**	**DP**	**SP**	**DP**	**SP**
Human	96.00		99.00		97.00	
InstructBLIP-7B	65.67	0.00	79.00	0.00	60.33	0.33
InstructBLIP-13B	66.33	68.67	84.33	80.00	45.00	49.67
Qwen-VL	64.00	4.33	83.33	8.67	59.00	24.67
Qwen-VL-Chat	69.67	69.00	87.00	86.67	78.33	82.67
LLaVA-7B	70.00	65.33	85.00	84.33	31.00	76.00
LLaVA-13B	72.67	70.33	90.00	90.00	75.00	**88.00**
InternVL-Chat-1.5-24B	**80.00**	77.33	**94.67**	92.00	79.33	77.67
LLaVA-Next-34B	**78.33**	75.33	93.33	**95.33**	85.33	84.00
Gemini-Pro	51.00	50.67	71.00	68.67	48.33	63.33
Qwen-VL-Max	76.67	**81.33**	93.67	**96.00**	**86.67**	**90.67**
GPT4V	69.33	67.00	82.67	79.33	68.33	69.00
GPT4o	68.00	67.67	83.00	81.67	78.00	82.67

E.3 A breakdown of Table 9

Table 14: *3D tabletop scene*

	what attribute move		what attribute rotate		what move		what rotate		where move		where rotate	
	DP	**SP**	**DP**	**SP**	**DP**	**SP**	**DP**	**SP**	**DP**	**SP**	**DP**	**SP**
Human	100.00		100.00		98.00		92.00		100.00		100.00	
VIDEO-CHATGPT-7B	27.00	24.33	27.00	28.33	18.33	19.00	15.67	18.67	27.33	26.33	13.33	11.67
VIDEO-LLAVA-7B	28.33	54.00	25.00	49.33	26.00	**34.00**	26.67	**35.33**	25.00	31.33	25.00	28.67
VIDEOCHAT2-7B	46.67	48.33	41.33	47.67	29.00	22.33	27.67	19.67	17.00	14.00	22.00	19.33
VIDEO-LLAMA-2-7B	28.67	24.00	27.67	25.00	22.33	19.00	23.33	16.00	20.00	7.33	20.67	6.67
VIDEO-LLAMA-2-13B	29.67	26.67	32.33	32.00	18.33	17.67	19.33	17.67	17.67	14.67	18.67	12.67
CHAT-UNIVI-7B	36.67	27.67	35.33	39.67	27.67	20.33	28.33	24.00	25.67	24.00	24.67	20.00
CHAT-UNIVI-13B	33.67	31.33	33.67	37.00	24.33	22.67	29.33	28.00	25.33	16.33	22.67	18.67
INTERNVL-CHAT-1.5-24B	52.33	43.00	56.00	49.33	26.67	21.00	31.33	22.67	31.67	28.00	32.00	26.00
LLAVA-NEXT-34B	**57.67**	**56.67**	59.00	**62.67**	28.00	29.33	30.67	29.67	**32.33**	**32.33**	**32.67**	**36.33**
GEMINI-PRO	39.33	38.67	40.33	37.67	**30.67**	28.67	27.33	25.33	27.67	29.67	25.33	20.67
QWEN-VL-MAX	**56.33**	52.67	**67.33**	**67.00**	29.00	30.00	34.00	**35.33**	26.00	25.00	20.67	26.33
GPT4V	43.67	51.00	46.67	57.33	28.00	29.33	29.67	32.00	22.00	26.00	15.67	25.33
GPT4O	47.67	46.00	54.67	**62.67**	27.33	**31.00**	34.33	**38.67**	27.00	**36.33**	23.00	**35.67**

Table 15: Real videos with *Scene Graph*

	what action		what object		what relation	
	DP	**SP**	**DP**	**SP**	**DP**	**SP**
Human	100.00		98.00		100.00	
VIDEO-CHATGPT-7B	19.67	16.33	37.00	29.67	34.67	31.00
VIDEO-LLAVA-7B	29.67	58.33	31.33	62.67	35.33	49.00
VIDEOCHAT2-7B	36.33	26.33	44.33	42.67	33.00	29.67
VIDEO-LLAMA-2-7B	33.67	21.33	37.67	40.00	37.67	33.67
VIDEO-LLAMA-2-13B	30.33	23.67	39.00	36.00	23.00	25.67
CHAT-UNIVI-7B	44.67	37.67	57.33	47.67	48.33	49.67
CHAT-UNIVI-13B	38.33	25.00	58.67	52.00	38.67	42.67
INTERNVL-CHAT-1.5-24B	**72.33**	52.33	**73.00**	54.33	59.00	62.33
LLAVA-NEXT-34B	67.00	60.00	67.33	65.33	68.33	65.00
GEMINI-PRO	54.33	39.67	55.00	53.00	40.67	44.67
QWEN-VL-MAX	**67.33**	**68.67**	**69.67**	**68.00**	70.33	63.67
GPT4V	53.67	56.67	57.67	58.67	66.00	**72.67**
GPT4O	64.67	62.33	66.00	60.00	**78.00**	**76.33**

F Details of Experiments on Query Results Approximation Algorithms

To experiment with different query results approximation approaches, we first conduct extensive experiments to evaluate a set of representative models against a subset of tasks for each task generator. Then, we build an Oracle database with the obtained evaluation results, referred to as TASK-ME-ANYTHING-DB, and study different query results approximation methods with this Oracle database to verify their effectiveness. We will release the TASK-ME-ANYTHING-DB for future studies of query results approximation or model performance prediction.

F.1 Experiment details

Setup. For image question answering tasks, We select 6 representative open-sourced large multi-modal language models (MLMs) from 3 model families: INSTRUCTBLIP-7B and INSTRUCTBLIP-13B from INSTRUCTBLIP [18], QWEN-VL and QWEN-VL-CHAT from QWEN-VL [6], and LLAVA-7B and LLAVA-13B from LLAVA [58]. For video question answering tasks, We select 7 representative open-sourced Large Video Language Models from 5 model families: VIDEO-LLAMA-2-7B and VIDEO-LLAMA-2-13B from VIDEO-LLAMA-2 [100], VIDEO-CHATGPT-7B from VIDEO-CHATGPT [65], CHAT-UNIVI-7B and CHAT-UNIVI-13B from CHAT-UNIVI [42], VIDEO-LLAVA-7B from VIDEO-LLAVA [55], and VIDEOCHAT2-7B from VIDEOCHAT2 [53]. We evaluate the models against a subset of tasks whose statistics can be found in Table 16. Since we generate 15 task instances for each task and involve multiple models, these lead to a total number of 24,240,780 <model, task instance> pairs in evaluation. We evaluate the query results approximation methods on a series of query instances for each type of query. These query instances cover all the subsets of tasks and models we evaluate, leading to a set of 1137 query instances in total (741 for ImageQA and 396 for VideoQA). We set the budget to 2,000 task evaluations.

Table 16: **Statistics of evaluated tasks.** For each task, we generate 15 task instances for evaluation.

	Scenerio	Task generator	# of tasks
ImageQA	***2D sticker image***	how many	17,238
		what	12,740
		where	12,740
		what attribute	12,740
		where attribute	12,740
	3D tabletop scene	how many	17,238
		what	12,740
		where	12,740
		what attribute	12,740
		where attribute	12,740
		what size	10,304
		what attribute size	7,840
		where size	10,304
		what distance	6,160
		what attribute distance	6,000
		where distance	6,160
	real image w *Scene Graph*	what object	10,000
		what attribute	10,000
		what relation	10,000
Total number of tasks: 144,966			
VideoQA	***3D tabletop scene***	what rotate video	2,464
		what attribute rotate video	7,840
		where rotate video	2,464
		what distance video	4,928
		what attribute distance video	15,680
		where distance video	4,928
	Real video w *Scene Graph*	what object video	10,000
		what action video	10,000
		what relation video	10,000
Total number of tasks: 106,608			

Evaluation metrics. To evaluate the query results approximation methods, we adopt different evaluation metrics for different types of queries. For Top-K queries, we report the Mean Rank and the Hit Rate: Mean Rank is the average of the ground truth rank of the K items returned by the query results approximation method, so a lower Mean Rank indicates the returned items are actually ranked higher and the query results approximation method is better; Hit Rate measures the percentage of the K returned items are actual Top-K items, so the higher is the better. For the Threshold query and its variants (Model Comparison and Model Debugging query), we can treat them as a binary classification problem and adopt the Prediction, Recall, and F1-score as evaluation metrics.

F.2 Experiments on approximations under different budgets.

To evaluate the performance of approximation algorithms under different budgets, we conducted an experiment using QWEN-VL-CHAT as the target model on 2D how-many tasks. We tested three query approximation algorithms on four types of queries: Top-K query, Threshold query, Model comparison query, and Model debugging query. The experiments were performed under budgets of $1,000$, $2,000$, and $3,000$. The results of the experiment can be found in Table 17, 18, 19, and 20.

The results demonstrate that the *Active* approximation algorithm consistently outperforms the *Random* and *Fitting* algorithms across all query types and budget levels. In particular, for the Model Compare query, *Active* achieves better results with a 2,000 budget than baselines with larger budgets. Also, we can see the performance increase rapidly with more budget, indicating that users could have more accurate results when using a larger budget

Table 17: The performance of Top-K query results approximation algorithms with different budgets.

Budget	Random		Fitting		Active	
	MR	HR (%)	MR	HR (%)	MR	HR (%)
1,000	137.1	0.0	143.3	10.0	44.3	20.0
2,000	116.6	0.0	121.8	0.0	32.2	20.0
3,000	110.3	10.0	121.4	10.0	21.4	20.0

Table 18: The performance of Threshold query results approximation algorithms with different budgets.

Budget	Random			Fitting			Active		
	P (%)	R (%)	F1 (%)	P (%)	R (%)	F1 (%)	P (%)	R (%)	F1 (%)
1,000	42.61	31.82	36.43	48.48	10.39	17.11	45.0	11.69	18.56
2,000	43.90	35.06	38.99	43.44	34.42	38.41	43.44	34.42	38.41
3,000	45.38	38.31	41.55	45.89	43.51	44.67	50.93	71.43	59.46

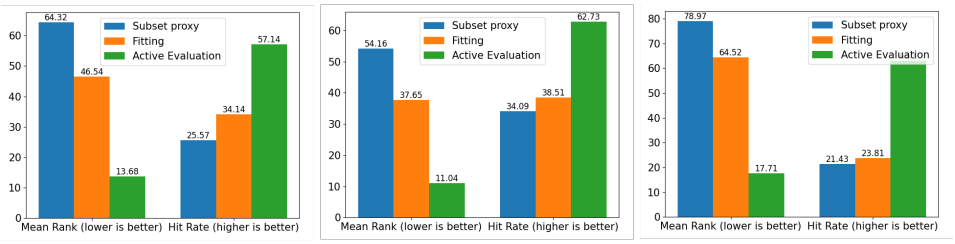
Table 19: The performance of Model comparison query results approximation algorithms with different budgets.

Budget	Random			Fitting			Active		
	P (%)	R (%)	F1 (%)	P (%)	R (%)	F1 (%)	P (%)	R (%)	F1 (%)
1,000	100.0	5.86	11.08	88.34	6.73	12.51	61.22	28.71	39.09
2,000	100.0	11.37	20.42	62.88	31.82	42.26	75.18	41.44	53.43
3,000	100.0	17.41	29.66	69.74	43.19	53.35	82.81	52.30	64.11

Table 20: The performance of Model debugging query results approximation algorithms with different budgets.

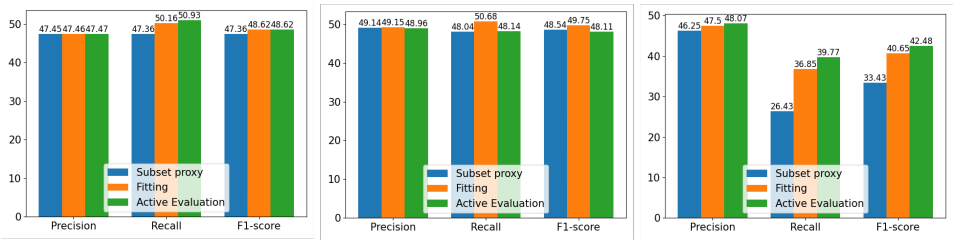
Budget	Random			Fitting			Active		
	P (%)	R (%)	F1 (%)	P (%)	R (%)	F1 (%)	P (%)	R (%)	F1 (%)
1,000	100.0	6.34	11.92	100.0	6.34	11.92	100.0	6.93	12.96
2,000	100.0	13.50	23.79	97.18	13.58	23.83	100.0	15.0	26.09
3,000	100.0	18.82	31.68	95.29	19.13	31.87	100.0	22.01	36.08

F.3 Query results approximation experiments in ImageQA



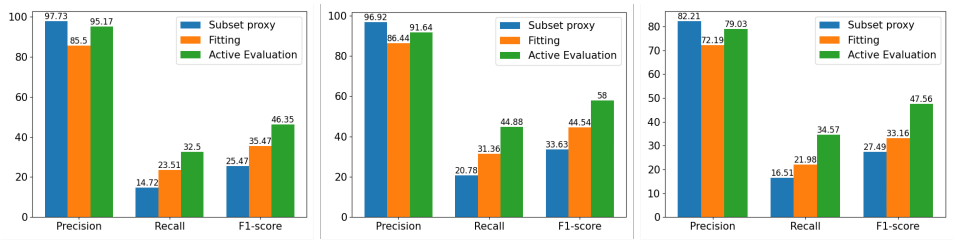
(a) 2D sticker image (b) 3D tabletop scene (c) Scene Graph w real images

Figure 23: **Top-K Query.** These three bar graphs display the performance of three query approximation methods in Top-K Query, measured by Mean Rank and Hit Rate.



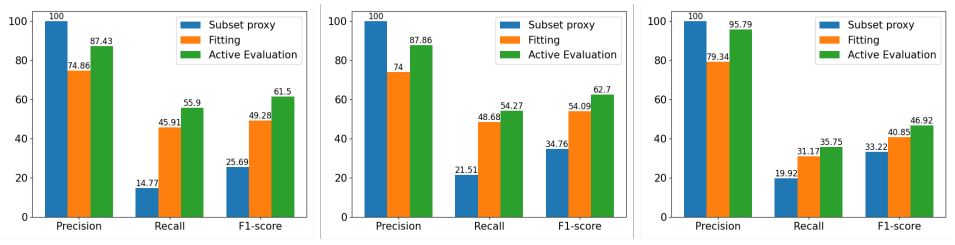
(a) 2D sticker image (b) 3D tabletop scene (c) Scene Graph w real images

Figure 24: **Threshold Query.** These three bar graphs display the performance of three query approximation methods in Threshold Query, measured by Precision, Recall, and F1-score.



(a) 2D sticker image (b) 3D tabletop scene (c) Scene Graph w real images

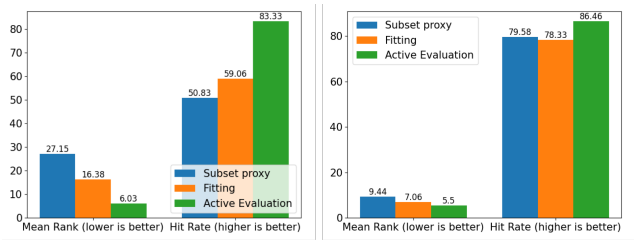
Figure 25: **Model Debugging Query.** These three bar graphs display the performance of three query approximation methods in Model Debugging Query, measured by Precision, Recall, and F1-score.



(a) 2D sticker image (b) 3D tabletop scene (c) Scene Graph w real images

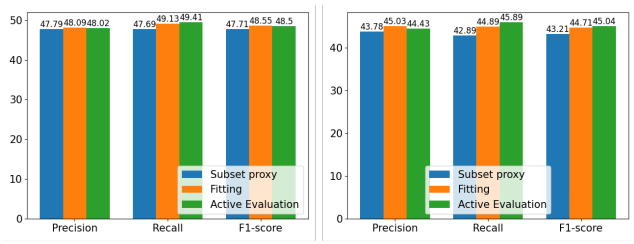
Figure 26: **Model Comparison Query.** These three bar graphs display the performance of three query approximation methods in Model Comparison Query, measured by Precision, Recall, and F1-score.

F.4 Query results approximation experiments in VideoQA



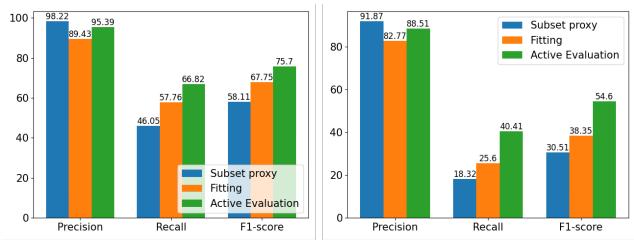
(a) 3D tabletop video (b) Scene Graph w real video

Figure 27: **Top-K Query in VideoQA.** These three bar graphs display the performance of three query approximation methods in Top-K Query, measured by Mean Rank and Hit Rate.



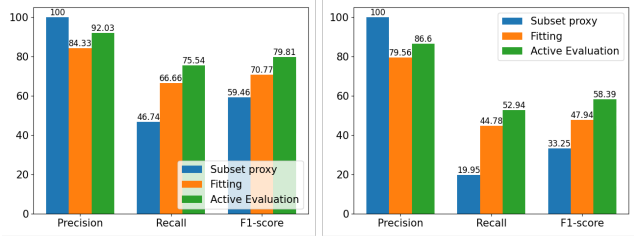
(a) 3D tabletop video (b) Scene Graph w real video

Figure 28: **Threshold Query in VideoQA.** These three bar graphs display the performance of three query approximation methods in Threshold Query, measured by Precision, Recall, and F1-score.



(a) 3D tabletop video (b) Scene Graph w real video

Figure 29: **Model Debugging Query in VideoQA.** These three bar graphs display the performance of three query approximation methods in Model Debugging Query, measured by Precision, Recall, and F1-score.



(a) 3D tabletop video (b) Scene Graph w real video

Figure 30: **Model Comparison Query in VideoQA.** These three bar graphs display the performance of three query approximation methods in Model Comparison Query, measured by Precision, Recall, and F1-score.

G Details of Analysis and Case Study

G.1 What task metadata are models good or bad at?

To obtain a more finegrained understanding of models' skill sets, we also leverage our interface to examine the top and bottom task metadata related to models' best and worst skills. For example, as QWEN-VL-CHAT performs the best on relation understanding across models and skills, we identify the top 20 relations where QWEN-VL-CHAT achieves the highest accuracies (Figure 31) and find that they are mostly actions. Similarly, on VideoQA tasks related to attribute understanding, we are also able to find the attribute values VIDEOCHAT2-7B is the best at and learn that they are mostly associated with color instead of shape or material (Figure 32). On the other hand, we learn that INSTRUCTBLIP-13B does terribly on spatial understanding especially when the object's absolute position is in the back, followed by front right or left (Figure 33); and among the actions VIDEO-LLAMA-2-13B performs the worst on, most involve "putting" or "throwing" something (Figure 34).

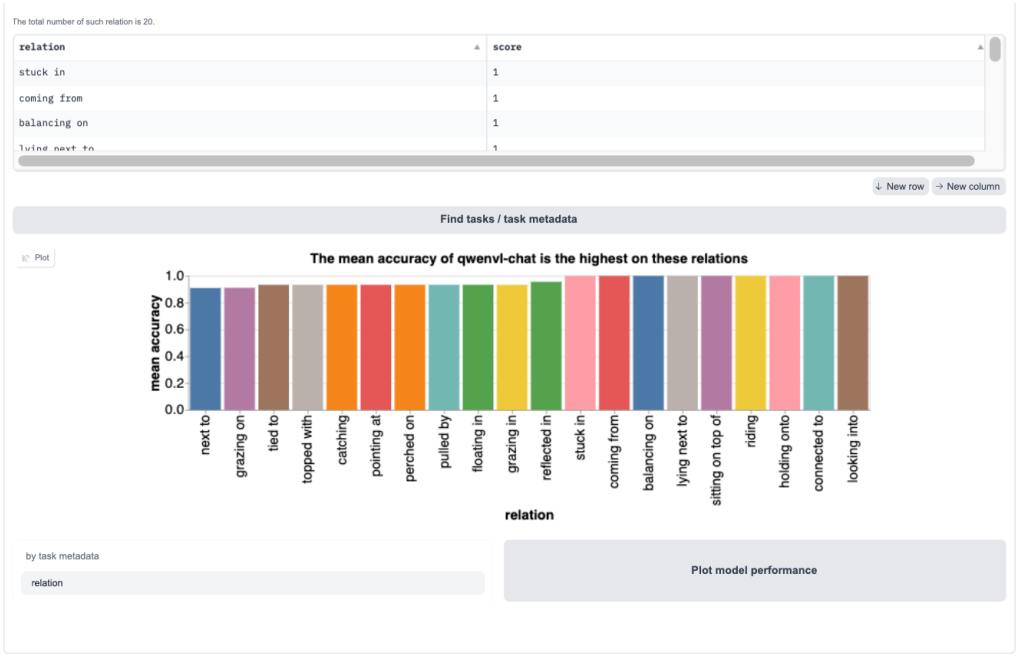


Figure 31: ImageQA: Best relations

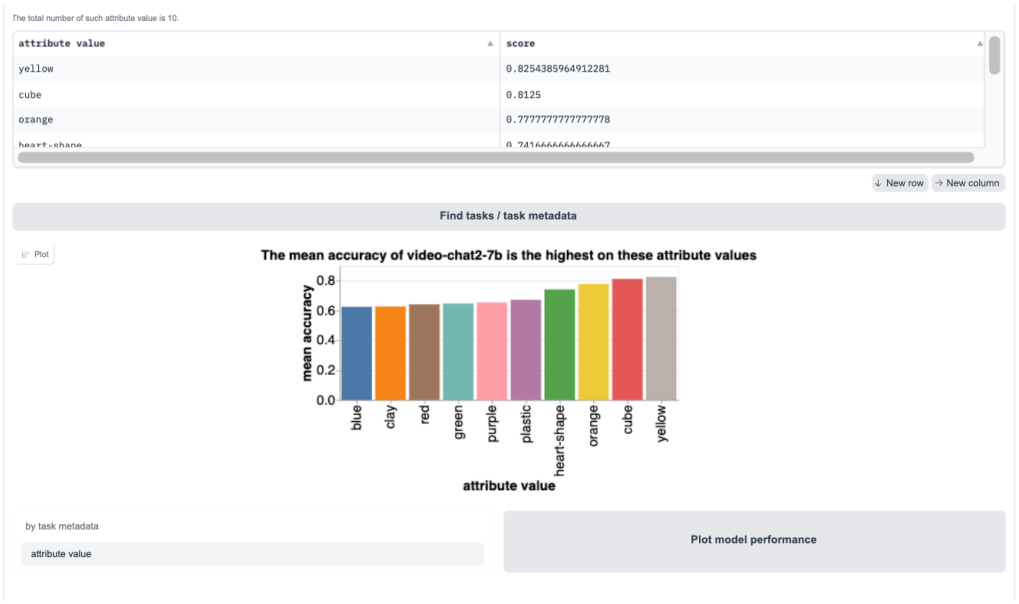


Figure 32: VideoQA: Best attributes

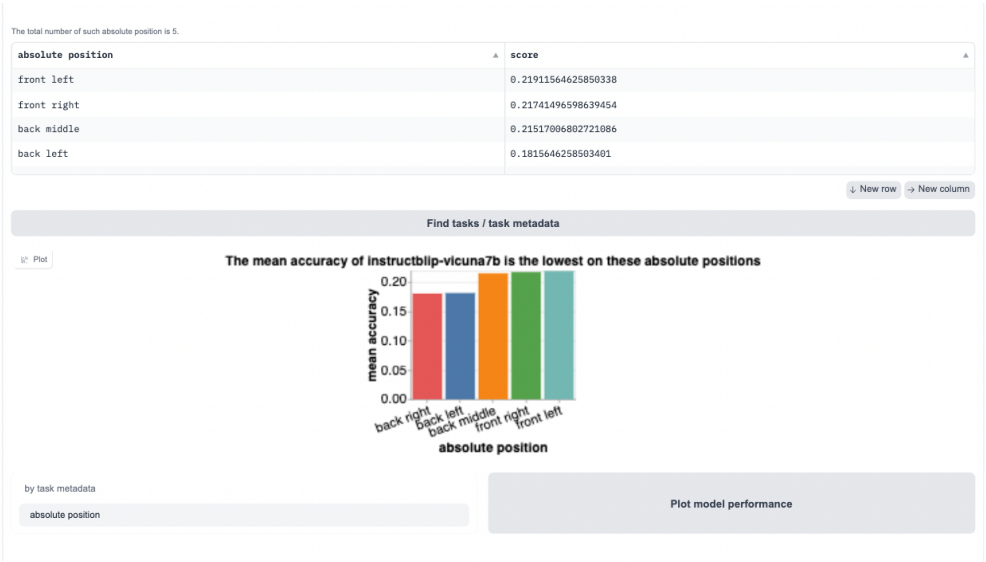


Figure 33: ImageQA: Worst positions

Figure 34: VideoQA: Worst actions

G.2 How do small models compare against large models? (continued)

As discussed in the main paper, we observe that large multi-modal models collectively perform better than smaller models on ImageQA tasks (Figure 12). Nevertheless, this finding might not always hold for individual models. Through t-tests with pairs of small and large models from the same source, we find one exception: INSTRUCTBLIP-7B ($\mu = 0.63$) significantly outperforms INSTRUCTBLIP-13B ($\mu = 0.49$) on relation understanding (with p-value = 0) (Figure 14).

Further, upon a closer look with our interface, we identify a few relations where INSTRUCTBLIP-7B outperforms INSTRUCTBLIP-13B by a large margin e.g. 50% (Figure 35). Similarly, we also retrieve a few actions and objects where VIDEO-LLAMA-2-7B performs much better e.g. by 20% than VIDEO-LLAMA-2-13B (Figures 36 and 37).

Figure 35: INSTRUCTBLIP-7B vs. INSTRUCTBLIP-13B relations

Figure 36: VIDEO-LLAMA-2-7B vs. VIDEO-LLAMA-2-13B actions

Figure 37: VIDEO-LLAMA-2-7B vs. VIDEO-LLAMA-2-13B objects

G.3 Do TASK-ME-ANYTHING yield results similar to existing benchmarks?

To check whether our TASK-ME-ANYTHING reflects model performance similarly to an existing benchmark, we conducted a case study testing six open-source models on both the well-known TallyQA Counting benchmark [2] (we selected 10,000 simple questions and 10,000 complex from the whole set) and 2D how-many and 3D how-many tasks in TASK-ME-ANYTHING-RANDOM. (Table 21), the results demonstrate a notable correlation. For instance, the LLAVA-13B is the best-performing model in both TallyQA and how-many tasks in TASK-ME-ANYTHING-RANDOM. The Spearman ranking coefficient for the correlation between the 2D how-many tasks and TallyQA is 0.714 (p-value = 0.111), while for the 3D how-many tasks, it is 0.543 (p-value = 0.266). These results indicate positive correlations of model performance between our tasks and existing ones, validating that TASK-ME-ANYTHING can effectively reflect model performance in a manner similar to existing benchmark.

Table 21: Models performance on TallyQA Counting benchmark and 2D how-many and 3D how-many in our TASK-ME-ANYTHING-RANDOM

Model	TallyQA	2D How Many	3D How Many
LLAVA-7B	35.90	42.00	38.67
LLAVA-13B	**38.33**	**49.33**	**46.67**
QWEN-VL	18.79	30.67	32.33
QWEN-VL-CHAT	32.07	39.67	45.00
INSTRUCTBLIP-7B	29.92	23.67	32.67
INSTRUCTBLIP-13B	33.22	26.67	32.00

H Datasheet for TASK-ME-ANYTHING-RANDOM

H.1 Motivation

1. **For what purpose was the dataset created?**
   TASK-ME-ANYTHING-RANDOM is created as a randomly selected subset of TASK-ME-ANYTHING-V1.0 to provide an overview of TASK-ME-ANYTHING.
2. **Who created the dataset and on behalf of which entity?**
   It was created by the authors of this paper.
3. **Who funded the creation of the dataset?**
   The creation of the dataset was funded by the institute to which the authors belong.

H.2 Composition

1. **What do the instances that comprise the dataset represent (e.g., documents, photos, people, countries?)**
   The dataset consists of 2D and 3D synthetic images, videos, and real images and videos, each accompanied by corresponding task plans, questions, options, and ground truths.
2. **How many instances are there in total (of each type, if appropriate)?**
   ImageQA: 5,700 instances (19 types of task generators, each with 300 instances per split per generator type). VideoQA: 2,700 instances (9 types of task generators, each with 300 instances per split per generator type).
3. **Does the dataset contain all possible instances, or is it a sample of instances from a larger set?**
   This dataset is a randomly selected subset from the TASK-ME-ANYTHING-V1.0 task space. Additional tasks can be generated by users based on their needs.
4. **Is there a label or target associated with each instance?**
   Yes, each instance includes both input and targets.
5. **Is any information missing from individual instances?**
   No.
6. **Are there recommended data splits (e.g., training, development/validation, testing)?**
   For ImageQA, there are 19 splits, each containing 300 instances from a specific task type. For VideoQA, there are 9 splits, each also containing 300 instances from a specific task type.
7. **Are there any errors, sources of noise, or redundancies in the dataset?**
   For real images and videos, the scene graphs may contain a small amount of noise due to human annotation bias. However, this does not have a significant impact on the research.
8. **Is the dataset self-contained, or does it link to or otherwise rely on external resources (e.g., websites, tweets, other datasets)?**
   The 3D objects used in the 2D sticker and 3D table scenarios are sourced from Objaverse. The real image scenarios are derived from the GQA versions of Visual Genome (VG), and the real videos are obtained from AGQA.
9. **Does the dataset contain data that might be considered confidential?**
   No.
10. **Does the dataset contain data that, if viewed directly, might be offensive, insulting, threatening, or might otherwise cause anxiety?**
    No.

H.3 Collection Process

1. **How was the data associated with each instance acquired?**
   The 3D objects used in the 2D sticker and 3D table scenarios are sourced from Objaverse. The real image scenarios are derived from the GQA versions of VG, while the real videos are from AGQAs. References are provided in Section 3 of the main text.
2. **What mechanisms or procedures were used to collect the data (e.g., hardware apparatus or sensor, manual human curation, software program, software API)?**
   We used multiple NVIDIA A6000 and A100 GPUs to run Blender for rendering the synthetic

scenes. Questions, options, and ground truth were generated by task generators (Python code).

3. **Who was involved in the data collection process (e.g., students, crowdworkers, contractors) and how were they compensated (e.g., how much were crowdworkers paid)?**
   The authors of this paper were directly involved in the data collection process, annotating the attributes of 3d objects and build the taxonomy themselves.
4. **Over what timeframe was the data collected?**
   The final version of the dataset was generated in June, 2024.

H.4 Uses

1. **Has the dataset been used for any tasks already?**
   No, this dataset has not been used for any tasks yet.
2. **What (other) tasks could the dataset be used for?**
   This data can also be used in various computer vision tasks, such as localization, object detection, etc.
3. **Is there anything about the composition of the dataset or the way it was collected and preprocessed/cleaned/labeled that might impact future uses?**
   No.
4. **Are there tasks for which the dataset should not be used?**
   No.

H.5 Distribution

1. **Will the dataset be distributed to third parties outside of the entity (e.g., company, institution, organization) on behalf of which the dataset was created?**
   Yes, the dataset is open to the public.
2. **How will the dataset be distributed (e.g., tarball on website, API, GitHub)?**
   You can access our dataset via the links below:
   Dataset (ImageQA): https://huggingface.co/datasets/weikaih/TaskMeAnything-v1-videoqa-random
   Dataset (VideoQA): https://huggingface.co/datasets/weikaih/TaskMeAnything-v1-videoqa-random
   Code: https://github.com/JieyuZ2/TaskMeAnything
3. **Have any third parties imposed IP-based or other restrictions on the data associated with the instances?**
   No.
4. **Do any export controls or other regulatory restrictions apply to the dataset or to individual instances?**
   No.

H.6 Maintenance

1. **Who will be supporting/hosting/maintaining the dataset?**
   The authors of this paper will support, host, and maintain the dataset.
2. **How can the owner/curator/manager of the dataset be contacted (e.g., email address)?**
   The owner/curator/manager(s) of the dataset can be contacted through the following email: Jieyu Zhang (jieyuz2@cs.washington.edu)
3. **Is there an erratum?**
   No. If errors are found in the future, we will release errata on the Github repo for the dataset: (https://github.com/JieyuZ2/TaskMeAnything).
4. **Will the dataset be updated (e.g., to correct labeling errors, add new instances, delete instances)?**
   Yes, the datasets will be updated whenever necessary to ensure accuracy, and announcements will be made accordingly. These updates will be posted on the Github repo for the dataset: (https://github.com/JieyuZ2/TaskMeAnything).

5. **If the dataset relates to people, are there applicable limits on the retention of the data associated with the instances (e.g., were the individuals in question told that their data would be retained for a fixed period of time and then deleted?)**
   N/A
6. **Will older versions of the dataset continue to be supported/hosted/maintained?**
   Yes. Older versions of the dataset will continue to be maintained and hosted.
7. **If others want to extend/augment/build on/contribute to the dataset, is there a mechanism for them to do so?**
   Yes, one can extend the dataset by simply adding more source data and task generators, or by generating more instances from the existing task space.

I Task Generator Cards

WhatGridTaskGenerator

- **Basic Information**.
  - **Task Type**. ImageQA
  - **Question Type**. what object
  - **Answer Type**. object category
  - **Image Type**. 2D sticker image
  - **The model capability to evaluate**. object recognition with / without reference
- **Source Data**.
  - rendering images of objects from Objaverse
  - Annotations regarding object category, attribute, and shape
- **Task Plan Schema**.
  - **question type**: `string`. The question type of these tasks will be "what".
  - **grid number**: `integer`. The number of diagonal grids of the image, N indicates there are $N \times N$ grids in the image. Support $\{2, 3\}$.
  - **target category**: `string`. The category name of the target object.
  - **absolute position**: `string`. The absolute position of the target object in the grid. It is a number ranging from 0 to 3 (grid number = 2) or 0 to 8 (grid number = 3).
  - **reference category**: `string`. The category name of the object that is used to reference the target object.
  - **reference position**: `string`. The relative position of the target object from the reference object.
  - **attribute type**: `string`. The type of attributes of the target object, currently include: `color`, `material`, and `shape`.
  - **attribute value**: `string`. The value of the attributes of the target object.
- **Partitions**.
  - **Partition 1**.
    - **Template**
      - **Q**: What is the object in the <absolute pos> part of the image?
      - **A**: <target category>
    - **Example**
      - **Q**: What is the object in the bottom middle part of the image?
      - **A**: folding chair
  - **Partition 2**.
    - **Template**.
      - **Q**: What is the object <reference pos> the <reference category>?
      - **A**: <target category>
    - **Example**
      - **Q**: What is the object to the left of the telephone?
      - **A**: table lamp
- **Limitations**: The current setup is primarily designed for stationary objects and may not effectively assess dynamic scenarios or human actions, such as interactions with objects or motion-based tasks.
- **Recommendations**: A task generator includes compositional and contextual challenges that require deeper reasoning about object relation and recognition.

WhereGridTaskGenerator

- **Basic Information**.
  - **Task Type**. ImageQA
  - **Question Type**. what object
  - **Answer Type**. object category
  - **Image Type**. 2D sticker image
  - **The model capability to evaluate**. object recognition with / without reference
- **Source Data**.
  - rendering images of objects from Objaverse
  - Annotations regarding object category, attribute, and shape
- **Task Plan Schema**.
  - **question type**: `string`. The question type of these tasks will be "what".
  - **grid number**: `integer`. The number of diagonal grids of the image, N indicates there are $N \times N$ grids in the image. Support $\{2, 3\}$.
  - **target category**: `string`. The category name of the target object.
  - **absolute position**: `string`. The absolute position of the target object in the grid. It is a number ranging from 0 to 3 (grid number = 2) or 0 to 8 (grid number = 3).
  - **reference category**: `string`. The category name of the object that is used to reference the target object.
  - **reference position**: `string`. The relative position of the target object from the reference object.
  - **attribute type**: `string`. The type of attributes of the target object, currently include: `color`, `material`, and `shape`.
  - **attribute value**: `string`. The value of the attributes of the target object.
- **Partitions**.
  - **Partition 1**.
    - **Template**
      - **Q**: Where is the <target category> in the image?
      - **A**: <absolute position>
    - **Example**
      - **Q**: Where is the apple in the image?
      - **A**: back left
  - **Partition 2**.
    - **Template**.
      - **Q**: Where is the <target category> with respect to the <reference category>?
      - **A**: <reference position>
    - **Example**
      - **Q**: Where is the vacuum cleaner with respect to the backpack?
      - **A**: left
- **Limitations**: The current setup is primarily designed for stationary objects and may not effectively assess dynamic scenarios or human actions, such as interactions with objects or motion-based tasks.
- **Recommendations**: A task generator includes compositional and contextual challenges that require deeper reasoning about object relation and recognition.

WhatAttributeGridTaskGenerator

- **Basic Information**.
  - **Task Type**. ImageQA
  - **Question Type**. what object
  - **Answer Type**. object category
  - **Image Type**. 2D sticker image
  - **The model capability to evaluate**. object recognition with / without reference
- **Source Data**.
  - rendering images of objects from Objaverse
  - Annotations regarding object category, attribute, and shape
- **Task Plan Schema**.
  - **question type**: `string`. The question type of these tasks will be "what attribute".
  - **grid number**: `integer`. The number of diagonal grids of the image, N indicates there are $N \times N$ grids in the image. Support $\{2, 3\}$.
  - **target category**: `string`. The category name of the target object.
  - **absolute position**: `string`. The absolute position of the target object in the grid. It is a number ranging from 0 to 3 (grid number = 2) or 0 to 8 (grid number = 3).
  - **reference category**: `string`. The category name of the object that is used to reference the target object.
  - **reference position**: `string`. The relative position of the target object from the reference object.
  - **attribute type**: `string`. The type of attributes of the target object, currently include: `color`, `material`, and `shape`.
  - **attribute value**: `string`. The value of the attributes of the target object.
- **Partitions**.
  - **Partition 1**.
    - **Template**
      - **Q**: What is the <attribute type> of the object in the <absolute position> part of the image?
      - **A**: <attribute value>
    - **Example**
      - **Q**: What is the material of the object in the middle part of the image?
      - **A**: plastic
  - **Partition 2**.
    - **Template**.
      - **Q**: What is the <attribute type> of the object to the left of the <reference category>?
      - **A**: <attribute value>
    - **Example**
      - **Q**: What is the color of the object to the left of the silverware?
      - **A**: gold
- **Limitations**: The current setup is primarily designed for stationary objects and may not effectively assess dynamic scenarios or human actions, such as interactions with objects or motion-based tasks.
- **Recommendations**: A task generator includes compositional and contextual challenges that require deeper reasoning about object relation and recognition.

WhereAttributeGridTaskGenerator

- **Basic Information**.
  - **Task Type**. ImageQA
  - **Question Type**. what object
  - **Answer Type**. object category
  - **Image Type**. 2D sticker image
  - **The model capability to evaluate**. object recognition with / without reference
- **Source Data**.
  - rendering images of objects from Objaverse
  - Annotations regarding object category, attribute, and shape
- **Task Plan Schema**.
  - **question type**: `string`. The question type of these tasks will be "where attribute".
  - **grid number**: `integer`. The number of diagonal grids of the image, N indicates there are $N \times N$ grids in the image. Support $\{2, 3\}$.
  - **target category**: `string`. The category name of the target object.
  - **absolute position**: `string`. The absolute position of the target object in the grid. It is a number ranging from 0 to 3 (grid number = 2) or 0 to 8 (grid number = 3).
  - **reference category**: `string`. The category name of the object that is used to reference the target object.
  - **reference position**: `string`. The relative position of the target object from the reference object.
  - **attribute type**: `string`. The type of attributes of the target object, currently include: `color`, `material`, and `shape`.
  - **attribute value**: `string`. The value of the attributes of the target object.
- **Partitions**.
  - **Partition 1**.
    - **Template**
      - **Q**: Where is the <attribute value> object in the image?
      - **A**: <absolute position>
    - **Example**
      - **Q**: Where is the white object in the image?
      - **A**: top right
  - **Partition 2**.
    - **Template**.
      - **Q**: Where is the <attribute value> object with respect to the <reference category>?
      - **A**: <absolute position>
    - **Example**
      - **Q**: Where is the gray object with respect to the lollipop?
      - **A**: top
- **Limitations**: The current setup is primarily designed for stationary objects and may not effectively assess dynamic scenarios or human actions, such as interactions with objects or motion-based tasks.
- **Recommendations**: A task generator includes compositional and contextual challenges that require deeper reasoning about object relation and recognition.

HowManyGridTaskGenerator

- **Basic Information**.
  - **Task Type**. ImageQA
  - **Question Type**. what object
  - **Answer Type**. object category
  - **Image Type**. 2D sticker image
  - **The model capability to evaluate**. object recognition with / without reference
- **Source Data**.
  - rendering images of objects from Objaverse
  - Annotations regarding object category, attribute, and shape
- **Task Plan Schema**.
  - **question type**: `string`. The question type of these tasks will be "how many".
  - **grid number**: `integer`. The number of diagonal grids of the image, N indicates there are $N \times N$ grids in the image. Support $\{2, 3\}$.
  - **target category**: `string`. The category name of the target object.
  - **count** `integer`. The total number of the target objects in the image.
  - **attribute type**: `string`. The type of attributes of the target object, currently include: `color`, `material`, and `shape`.
  - **attribute value**: `string`. The value of the attributes of the target object.
- **Partitions**.
  - **Partition 1**.
    - **Template**
      - **Q**: How many <attribute value> objects are there in the image?
      - **A**: <count>
    - **Example**
      - **Q**: How many blue objects are there in the image?
      - **A**: 2
  - **Partition 2**.
    - **Template**.
      - **Q**: How many <target category> are there in the image?
      - **A**: <count>
    - **Example**
      - **Q**: How many tables are there in the image?
      - **A**: 4
  - **Partition 3**.
    - **Template**.
      - **Q**: How many <attribute value> <target category> are there in the image?
      - **A**: <count>
    - **Example**
      - **Q**: How many pink beverages are there in the image?
      - **A**: 2
- **Limitations**: The current setup is primarily designed for stationary objects and may not effectively assess dynamic scenarios or human actions, such as interactions with objects or motion-based tasks.
- **Recommendations**: A task generator includes compositional and contextual challenges that require deeper reasoning about object relation and recognition.

What3DGridTaskGenerator

- **Basic Information**.
  - **Task Type**. ImageQA
  - **Question Type**. what object
  - **Answer Type**. object category
  - **Image Type**. 3D tabletop image
  - **The model capability to evaluate**. object recognition with / without reference
- **Source Data**.
  - rendering images of objects from Objaverse
  - Annotations regarding object category, attribute, and shape
- **Task Plan Schema**.
  - **question type**: `string`. The question type of these tasks will be "what".
  - **grid number**: `integer`. The number of diagonal grids of the image, N indicates there are $N \times N$ grids in the image. Support $\{2, 3\}$.
  - **target category**: `string`. The category name of the target object.
  - **absolute position**: `string`. The absolute position of the target object in the grid. It is a number ranging from 0 to 3 (grid number = 2) or 0 to 8 (grid number = 3).
  - **reference category**: `string`. The category name of the object that is used to reference the target object.
  - **reference position**: `string`. The relative position of the target object from the reference object.
  - **attribute type**: `string`. The type of attributes of the target object, currently include: `color`, `material`, and `shape`.
  - **attribute value**: `string`. The value of the attributes of the target object.
- **Partitions**.
  - **Partition 1**.
    - **Template**
      - **Q**: What is the object in the <absolute pos> part of the image?
      - **A**: <target category>
    - **Example**
      - **Q**: What is the object in the front right part of the image?
      - **A**: scale
  - **Partition 2**.
    - **Template**.
      - **Q**: What is the object <reference pos> the <reference category>?
      - **A**: <target category>
    - **Example**
      - **Q**: What is the object to the right of the mobile computer?
      - **A**: bucket
- **Limitations**: The current setup is primarily designed for stationary objects and may not effectively assess dynamic scenarios or human actions, such as interactions with objects or motion-based tasks.
- **Recommendations**: A task generator includes compositional and contextual challenges that require deeper reasoning about object relation and recognition.

Where3DGridTaskGenerator

- **Basic Information**.
  - **Task Type**. ImageQA
  - **Question Type**. what object
  - **Answer Type**. object category
  - **Image Type**. 3D tabletop image
  - **The model capability to evaluate**. object recognition with / without reference
- **Source Data**.
  - rendering images of objects from Objaverse
  - Annotations regarding object category, attribute, and shape
- **Task Plan Schema**.
  - **question type**: `string`. The question type of these tasks will be "where".
  - **grid number**: `integer`. The number of diagonal grids of the image, N indicates there are $N \times N$ grids in the image. Support $\{2, 3\}$.
  - **target category**: `string`. The category name of the target object.
  - **absolute position**: `string`. The absolute position of the target object in the grid. It is a number ranging from 0 to 3 (grid number = 2) or 0 to 8 (grid number = 3).
  - **reference category**: `string`. The category name of the object that is used to reference the target object.
  - **reference position**: `string`. The relative position of the target object from the reference object.
  - **attribute type**: `string`. The type of attributes of the target object, currently include: `color`, `material`, and `shape`.
  - **attribute value**: `string`. The value of the attributes of the target object.
- **Partitions**.
  - **Partition 1**.
    - **Template**
      - **Q**: Where is the <target category> in the image?
      - **A**: <absolute position>
    - **Example**
      - **Q**: Where is the vacuum cleaner in the image?
      - **A**: back left
  - **Partition 2**.
    - **Template**.
      - **Q**: Where is the <target category> with respect to the <reference category>?
      - **A**: <reference position>
    - **Example**
      - **Q**: Where is the vacuum cleaner with respect to the wine glass?
      - **A**: left
- **Limitations**: The current setup is primarily designed for stationary objects and may not effectively assess dynamic scenarios or human actions, such as interactions with objects or motion-based tasks.
- **Recommendations**: A task generator includes compositional and contextual challenges that require deeper reasoning about object relation and recognition.

WhatAttribute3DGridTaskGenerator

- **Basic Information**.
  - **Task Type**. ImageQA
  - **Question Type**. what object
  - **Answer Type**. object category
  - **Image Type**. 3D tabletop image
  - **The model capability to evaluate**. object recognition with / without reference
- **Source Data**.
  - rendering images of objects from Objaverse
  - Annotations regarding object category, attribute, and shape
- **Task Plan Schema**.
  - **question type**: `string`. The question type of these tasks will be "what attribute".
  - **grid number**: `integer`. The number of diagonal grids of the image, N indicates there are $N \times N$ grids in the image. Support $\{2, 3\}$.
  - **target category**: `string`. The category name of the target object.
  - **absolute position**: `string`. The absolute position of the target object in the grid. It is a number ranging from 0 to 3 (grid number = 2) or 0 to 8 (grid number = 3).
  - **reference category**: `string`. The category name of the object that is used to reference the target object.
  - **reference position**: `string`. The relative position of the target object from the reference object.
  - **attribute type**: `string`. The type of attributes of the target object, currently include: `color`, `material`, and `shape`.
  - **attribute value**: `string`. The value of the attributes of the target object.
- **Partitions**.
  - **Partition 1**.
    - **Template**
      - **Q**: What is the <attribute type> of the object in the <absolute position> part of the image?
      - **A**: <attribute value>
    - **Example**
      - **Q**: What is the color of the object in the back left part of the image?
      - **A**: red
  - **Partition 2**.
    - **Template**.
      - **Q**: What is the <attribute type> of the object to the left of the <reference category>?
      - **A**: <attribute value>
    - **Example**
      - **Q**: What is the material of the object behind the plate?
      - **A**: wood
- **Limitations**: The current setup is primarily designed for stationary objects and may not effectively assess dynamic scenarios or human actions, such as interactions with objects or motion-based tasks.
- **Recommendations**: A task generator includes compositional and contextual challenges that require deeper reasoning about object relation and recognition.

WhereAttribute3DGridTaskGenerator

- **Basic Information**.
  - **Task Type**. ImageQA
  - **Question Type**. what object
  - **Answer Type**. object category
  - **Image Type**. 3D tabletop image
  - **The model capability to evaluate**. object recognition with / without reference
- **Source Data**.
  - rendering images of objects from Objaverse
  - Annotations regarding object category, attribute, and shape
- **Task Plan Schema**.
  - **question type**: `string`. The question type of these tasks will be "where attribute".
  - **grid number**: `integer`. The number of diagonal grids of the image, N indicates there are $N \times N$ grids in the image. Support $\{2, 3\}$.
  - **target category**: `string`. The category name of the target object.
  - **absolute position**: `string`. The absolute position of the target object in the grid. It is a number ranging from 0 to 3 (grid number = 2) or 0 to 8 (grid number = 3).
  - **reference category**: `string`. The category name of the object that is used to reference the target object.
  - **reference position**: `string`. The relative position of the target object from the reference object.
  - **attribute type**: `string`. The type of attributes of the target object, currently include: `color`, `material`, and `shape`.
  - **attribute value**: `string`. The value of the attributes of the target object.
- **Partitions**.
  - **Partition 1**.
    - **Template**
      - **Q**: Where is the <attribute value> object in the image?
      - **A**: <absolute position>
    - **Example**
      - **Q**: Where is the wood object in the image?
      - **A**: front right
  - **Partition 2**.
    - **Template**.
      - **Q**: Where is the <attribute value> object with respect to the <reference category>?
      - **A**: <absolute position>
    - **Example**
      - **Q**: Where is the white object with respect to the trophy?
      - **A**: left
- **Limitations**: The current setup is primarily designed for stationary objects and may not effectively assess dynamic scenarios or human actions, such as interactions with objects or motion-based tasks.
- **Recommendations**: A task generator includes compositional and contextual challenges that require deeper reasoning about object relation and recognition.

HowMany3DGridTaskGenerator

- **Basic Information**.
  - **Task Type**. ImageQA
  - **Question Type**. what object
  - **Answer Type**. object category
  - **Image Type**. 3D tabletop image
  - **The model capability to evaluate**. object recognition with / without reference
- **Source Data**.
  - rendering images of objects from Objaverse
  - Annotations regarding object category, attribute, and shape
- **Task Plan Schema**.
  - **question type**: `string`. The question type of these tasks will be "how many".
  - **grid number**: `integer`. The number of diagonal grids of the image, N indicates there are $N \times N$ grids in the image. Support $\{2, 3\}$.
  - **target category**: `string`. The category name of the target object.
  - **count** `integer`. The total number of the target objects in the image.
  - **attribute type**: `string`. The type of attributes of the target object, currently include: `color`, `material`, and `shape`.
  - **attribute value**: `string`. The value of the attributes of the target object.
- **Partitions**.
  - **Partition 1**.
    - **Template**
      - **Q**: How many <attribute value> objects are there in the image?
      - **A**: <count>
    - **Example**
      - **Q**: How many blue objects are there in the image?
      - **A**: 6
  - **Partition 2**.
    - **Template**.
      - **Q**: How many <target category> are there in the image?
      - **A**: <count>
    - **Example**
      - **Q**: How many plates are there in the image?
      - **A**: 5
  - **Partition 3**.
    - **Template**.
      - **Q**: How many <attribute value> <target category> are there in the image?
      - **A**: <count>
    - **Example**
      - **Q**: How many black furnitures are there in the image?
      - **A**: 4
- **Limitations**: The current setup is primarily designed for stationary objects and may not effectively assess dynamic scenarios or human actions, such as interactions with objects or motion-based tasks.
- **Recommendations**: A task generator includes compositional and contextual challenges that require deeper reasoning about object relation and recognition.

WhatDistance3DGridTaskGenerator

- **Basic Information**.
  - **Task Type**. ImageQA
  - **Question Type**. what object
  - **Answer Type**. object category
  - **Image Type**. 3D tabletop image
  - **The model capability to evaluate**. object recognition with / without reference
- **Source Data**.
  - rendering images of objects from Objaverse
  - Annotations regarding object category, attribute, and shape
- **Task Plan Schema**.
  - **question type**: `string`. The question type of these tasks will be "what distance".
  - **distance type**: `string`. The type of the distance between target object and the reference object, indicates whether it pertains to the "farthest" or "closest" distance.
  - **grid number**: `integer`. The number of diagonal grids of the image, N indicates there are $N \times N$ grids in the image. Support $\{2, 3\}$.
  - **target category**: `string`. The category name of the target object.
  - **absolute position**: `string`. The absolute position of the target object in the grid. It is a number ranging from 0 to 3 (grid number = 2) or 0 to 8 (grid number = 3).
  - **reference category**: `string`. The category name of the object that is used to reference the target object.
  - **reference position**: `string`. The relative position of the target object from the reference object.
  - **attribute type**: `string`. The type of attributes of the target object, currently include: `color`, `material`, and `shape`.
  - **attribute value**: `string`. The value of the attributes of the target object.
- **Partitions**.
  - **Partition 1**.
    - **Template**
      - **Q**: What is the object that is <distance type> from the <reference category>?
      - **A**: <target category>
    - **Example**
      - **Q**: What is the object that is farthest from the optical instrument?
      - **A**: juice
- **Limitations**: The current setup is primarily designed for stationary objects and may not effectively assess dynamic scenarios or human actions, such as interactions with objects or motion-based tasks.
- **Recommendations**: A task generator includes compositional and contextual challenges that require deeper reasoning about object relation and recognition.

WhereDistance3DGridTaskGenerator

- **Basic Information**.
  - **Task Type**. ImageQA
  - **Question Type**. what object
  - **Answer Type**. object category
  - **Image Type**. 3D tabletop image
  - **The model capability to evaluate**. object recognition with / without reference
- **Source Data**.
  - rendering images of objects from Objaverse
  - Annotations regarding object category, attribute, and shape
- **Task Plan Schema**.
  - **question type**: `string`. The question type of these tasks will be "where distance".
  - **distance type**: `string`. The type of the distance between target object and the reference object, indicates whether it pertains to the "farthest" or "closest" distance.
  - **grid number**: `integer`. The number of diagonal grids of the image, N indicates there are $N \times N$ grids in the image. Support $\{2, 3\}$.
  - **target category**: `string`. The category name of the target object.
  - **absolute position**: `string`. The absolute position of the target object in the grid. It is a number ranging from 0 to 3 (grid number = 2) or 0 to 8 (grid number = 3).
  - **reference category**: `string`. The category name of the object that is used to reference the target object.
  - **reference position**: `string`. The relative position of the target object from the reference object.
  - **attribute type**: `string`. The type of attributes of the target object, currently include: `color`, `material`, and `shape`.
  - **attribute value**: `string`. The value of the attributes of the target object.
- **Partitions**.
  - **Partition 1**.
    - **Template**
      - **Q**: Where is the object that is <distance type> from the <reference category> in the image?
      - **A**: <reference position>
    - **Example**
      - **Q**: Where is the object that is farthest from the bread in the image?
      - **A**: middle
- **Limitations**: The current setup is primarily designed for stationary objects and may not effectively assess dynamic scenarios or human actions, such as interactions with objects or motion-based tasks.
- **Recommendations**: A task generator includes compositional and contextual challenges that require deeper reasoning about object relation and recognition.

WhatAttributeDistance3DGridTaskGenerator

- **Basic Information**.
  - **Task Type**. ImageQA
  - **Question Type**. what object
  - **Answer Type**. object category
  - **Image Type**. 3D tabletop image
  - **The model capability to evaluate**. object recognition with / without reference
- **Source Data**.
  - rendering images of objects from Objaverse
  - Annotations regarding object category, attribute, and shape
- **Task Plan Schema**.
  - **question type**: `string`. The question type of these tasks will be "what attribute distance".
  - **distance type**: `string`. The type of the distance between target object and the reference object, indicates whether it pertains to the "farthest" or "closest" distance.
  - **grid number**: `integer`. The number of diagonal grids of the image, N indicates there are $N \times N$ grids in the image. Support $\{2, 3\}$.
  - **target category**: `string`. The category name of the target object.
  - **absolute position**: `string`. The absolute position of the target object in the grid. It is a number ranging from 0 to 3 (grid number = 2) or 0 to 8 (grid number = 3).
  - **reference category**: `string`. The category name of the object that is used to reference the target object.
  - **reference position**: `string`. The relative position of the target object from the reference object.
  - **attribute type**: `string`. The type of attributes of the target object, currently include: `color`, `material`, and `shape`.
  - **attribute value**: `string`. The value of the attributes of the target object.
- **Partitions**.
  - **Partition 1**.
    - **Template**
      - **Q**: What is the <attribute type> of the object that is <distance type> to the <target category>?
      - **A**: <attribute value>
    - **Example**
      - **Q**: What is the color of the object that is closest to the statue?
      - **A**: beige
- **Limitations**: The current setup is primarily designed for stationary objects and may not effectively assess dynamic scenarios or human actions, such as interactions with objects or motion-based tasks.
- **Recommendations**: A task generator includes compositional and contextual challenges that require deeper reasoning about object relation and recognition.

WhatSize3DGridTaskGenerator

- **Basic Information**.
  - **Task Type**. ImageQA
  - **Question Type**. what object
  - **Answer Type**. object category
  - **Image Type**. 3D tabletop image
  - **The model capability to evaluate**. object recognition with / without reference
- **Source Data**.
  - rendering images of objects from Objaverse
  - Annotations regarding object category, attribute, and shape
- **Task Plan Schema**.
  - **question type**: `string`. The question type of these tasks will be "what size".
  - **size**: `string`. The type of the size of the target object, indicates whether it pertains to the "largest" or "smallest" in all the objects.
  - **grid number**: `integer`. The number of diagonal grids of the image, N indicates there are $N \times N$ grids in the image. Support $\{2, 3\}$.
  - **target category**: `string`. The category name of the target object.
  - **absolute position**: `string`. The absolute position of the target object in the grid. It is a number ranging from 0 to 3 (grid number = 2) or 0 to 8 (grid number = 3).
  - **attribute type**: `string`. The type of attributes of the target object, currently include: `color`, `material`, and `shape`.
  - **attribute value**: `string`. The value of the attributes of the target object.
- **Partitions**.
  - **Partition 1**.
    - **Template**
      - **Q**: What is the <size> object in the image?
      - **A**: <target category>
    - **Example**
      - **Q**: What is the smallest object in the image?
      - **A**: spatula
- **Limitations**: The current setup is primarily designed for stationary objects and may not effectively assess dynamic scenarios or human actions, such as interactions with objects or motion-based tasks.
- **Recommendations**: A task generator includes compositional and contextual challenges that require deeper reasoning about object relation and recognition.

WhereSize3DGridTaskGenerator

- **Basic Information**.
  - **Task Type**. ImageQA
  - **Question Type**. what object
  - **Answer Type**. object category
  - **Image Type**. 3D tabletop image
  - **The model capability to evaluate**. object recognition with / without reference
- **Source Data**.
  - rendering images of objects from Objaverse
  - Annotations regarding object category, attribute, and shape
- **Task Plan Schema**.
  - **question type**: `string`. The question type of these tasks will be "where size".
  - **size**: `string`. The type of the size of the target object, indicates whether it pertains to the "largest" or "smallest" in all the objects.
  - **grid number**: `integer`. The number of diagonal grids of the image, N indicates there are $N \times N$ grids in the image. Support $\{2, 3\}$.
  - **target category**: `string`. The category name of the target object.
  - **absolute position**: `string`. The absolute position of the target object in the grid. It is a number ranging from 0 to 3 (grid number = 2) or 0 to 8 (grid number = 3).
  - **reference category**: `string`. The category name of the object that is used to reference the target object.
  - **reference position**: `string`. The relative position of the target object from the reference object.
  - **attribute type**: `string`. The type of attributes of the target object, currently include: `color`, `material`, and `shape`.
  - **attribute value**: `string`. The value of the attributes of the target object.
  - **target-reference order**: `string`. Define the target object goes first or not in the question. It is related to grammar
- **Partitions**.
  - **Partition 1**.
    - **Template**
      - **Q**: Where is the <size> object in the image?
      - **A**: <absolute position>
    - **Example**
      - **Q**: Where is the largest object in the image?
      - **A**: middle
  - **Partition 2**.
    - **Template**
      - **Q**: Where is the <size> object in the image with respect to the <reference category>?
      - **A**: <reference position>
    - **Example**
      - **Q**: Where is the smallest object in the image with respect to the car?
      - **A**: middle
- **Limitations**: The current setup is primarily designed for stationary objects and may not effectively assess dynamic scenarios or human actions, such as interactions with objects or motion-based tasks.
- **Recommendations**: A task generator includes compositional and contextual challenges that require deeper reasoning about object relation and recognition.

WhatAttributeSize3DGridTaskGenerator

- **Basic Information**.
  - **Task Type**. ImageQA
  - **Question Type**. what object
  - **Answer Type**. object category
  - **Image Type**. 3D tabletop image
  - **The model capability to evaluate**. object recognition with / without reference
- **Source Data**.
  - rendering images of objects from Objaverse
  - Annotations regarding object category, attribute, and shape
- **Task Plan Schema**.
  - **question type**: `string`. The question type of these tasks will be "what attribute size".
  - **size**: `string`. The type of the size of the target object, indicates whether it pertains to the "largest" or "smallest" in all the objects.
  - **grid number**: `integer`. The number of diagonal grids of the image, N indicates there are $N \times N$ grids in the image. Support $\{2, 3\}$.
  - **target category**: `string`. The category name of the target object.
  - **absolute position**: `string`. The absolute position of the target object in the grid. It is a number ranging from 0 to 3 (grid number = 2) or 0 to 8 (grid number = 3).
  - **attribute type**: `string`. The type of attributes of the target object, currently include: `color`, `material`, and `shape`.
  - **attribute value**: `string`. The value of the attributes of the target object.
- **Partitions**.
  - **Partition 1**.
    - **Template**
      - **Q**: What is the <attribute type> of the <size> object in the image?
      - **A**: <attribute value>
    - **Example**
      - **Q**: What is the color of the smallest object in the image?
      - **A**: black
- **Limitations**: The current setup is primarily designed for stationary objects and may not effectively assess dynamic scenarios or human actions, such as interactions with objects or motion-based tasks.
- **Recommendations**: A task generator includes compositional and contextual challenges that require deeper reasoning about object relation and recognition.

WhatMovementVideoGridTaskGenerator

- **Basic Information**.
  - **Task Type**. VideoQA
  - **Question Type**. what object
  - **Answer Type**. object category
  - **Image Type**. 3D tabletop video
  - **The model capability to evaluate**. object recognition with / without reference
- **Source Data**.
  - rendering images of objects from Objaverse
  - Annotations regarding object category, attribute, and shape
- **Task Plan Schema**.
  - **question type**: `string`. The question type of these tasks will be "what move video".
  - **grid number**: `integer`. The number of diagonal grids of the image, N indicates there are $N \times N$ grids in the image. Support $\{2, 3\}$.
  - **target category**: `string`. The category name of the target object.
  - **absolute position**: `string`. The absolute position of the target object in the grid. It is a number ranging from 0 to 3 (grid number = 2) or 0 to 8 (grid number = 3).
  - **attribute type**: `string`. The type of attributes of the target object, currently include: `color`, `material`, and `shape`.
  - **attribute value**: `string`. The value of the attributes of the target object.
  - **moving direction**: `string`. The moving direction of the target object, can be either 'left', 'right', 'up', or 'down'.
  - **are other objects moving**: `string`. Indicates that other objects in the video are moving or not, can be "Yes" or "No". If it is "Yes" moving, it should not be in the same direction of the target object's moving direction.
- **Partitions**.
  - **Partition 1**.
    - **Template**
      - **Q**: What is the object that is moving <moving direction> in the video?
      - **A**: <target category>
    - **Example**
      - **Q**: What is the object that is moving left in the video?
      - **A**: serving tray
  - **Partition 2**.
    - **Template**
      - **Q**: What is the moving object in the video?
      - **A**: <target category>
    - **Example**
      - **Q**: What is the moving object in the video?
      - **A**: barrel
- **Limitations**: The current setup is primarily designed for stationary objects and may not effectively assess dynamic scenarios or human actions, such as interactions with objects or motion-based tasks.
- **Recommendations**: A task generator includes compositional and contextual challenges that require deeper reasoning about object relation and recognition.

WhereMovementVideoGridTaskGenerator

- **Basic Information**.
  - **Task Type**. VideoQA
  - **Question Type**. what object
  - **Answer Type**. object category
  - **Image Type**. 3D tabletop video
  - **The model capability to evaluate**. object recognition with / without reference
- **Source Data**.
  - rendering images of objects from Objaverse
  - Annotations regarding object category, attribute, and shape
- **Task Plan Schema**.
  - **question type**: `string`. The question type of these tasks will be "where move video".
  - **grid number**: `integer`. The number of diagonal grids of the image, N indicates there are $N \times N$ grids in the image. Support $\{2, 3\}$.
  - **target category**: `string`. The category name of the target object.
  - **absolute position**: `string`. The absolute position of the target object in the grid. It is a number ranging from 0 to 3 (grid number = 2) or 0 to 8 (grid number = 3).
  - **attribute type**: `string`. The type of attributes of the target object, currently include: `color`, `material`, and `shape`.
  - **attribute value**: `string`. The value of the attributes of the target object.
  - **moving direction**: `string`. The moving direction of the target object, can be either 'left', 'right', 'up', or 'down'.
  - **are other objects moving**: `string`. Indicates that other objects in the video are moving or not, can be "Yes" or "No". If it is "Yes" moving, it should not be in the same direction of the target object's moving direction.
- **Partitions**.
  - **Partition 1**.
    - **Template**
      - **Q**: Where is the object that is moving down located in the video?
      - **A**: <absolute position>
    - **Example**
      - **Q**: Where is the object that is moving down located in the video?
      - **A**: back right
  - **Partition 2**.
    - **Template**
      - **Q**: Where is the moving object located in the video?
      - **A**: <absolute position>
    - **Example**
      - **Q**: Where is the moving object located in the video?
      - **A**: back right
- **Limitations**: The current setup is primarily designed for stationary objects and may not effectively assess dynamic scenarios or human actions, such as interactions with objects or motion-based tasks.
- **Recommendations**: A task generator includes compositional and contextual challenges that require deeper reasoning about object relation and recognition.

WhatAttributeMovementVideoGridTaskGenerator

- **Basic Information**.
  - **Task Type**. VideoQA
  - **Question Type**. what object
  - **Answer Type**. object category
  - **Image Type**. 3D tabletop video
  - **The model capability to evaluate**. object recognition with / without reference
- **Source Data**.
  - rendering images of objects from Objaverse
  - Annotations regarding object category, attribute, and shape
- **Task Plan Schema**.
  - **question type**: `string`. The question type of these tasks will be "what attribute move video".
  - **size**: `string`. The type of the size of the target object, indicates whether it pertains to the "largest" or "smallest" in all the objects.
  - **grid number**: `integer`. The number of diagonal grids of the image, N indicates there are $N \times N$ grids in the image. Support $\{2, 3\}$.
  - **target category**: `string`. The category name of the target object.
  - **absolute position**: `string`. The absolute position of the target object in the grid. It is a number ranging from 0 to 3 (grid number = 2) or 0 to 8 (grid number = 3).
  - **attribute type**: `string`. The type of attributes of the target object, currently include: `color`, `material`, and `shape`.
  - **attribute value**: `string`. The value of the attributes of the target object.
- **Partitions**.
  - **Partition 1**.
    - **Template**
      - **Q**: What is the <attribute type> of the object that is moving <moving direction> in the video?
      - **A**: <attribute value>
    - **Example**
      - **Q**: What is the color of the object that is moving left in the video?
      - **A**: black
  - **Partition 2**.
    - **Template**
      - **Q**: Where is the <attribute type> of the moving object in the video?
      - **A**: <attribute value>
    - **Example**
      - **Q**: What is the color of the moving object in the video?
      - **A**: white
- **Limitations**: The current setup is primarily designed for stationary objects and may not effectively assess dynamic scenarios or human actions, such as interactions with objects or motion-based tasks.
- **Recommendations**: A task generator includes compositional and contextual challenges that require deeper reasoning about object relation and recognition.

WhatRotationVideoGridTaskGenerator

- **Basic Information**.
  - **Task Type**. VideoQA
  - **Question Type**. what object
  - **Answer Type**. object category
  - **Image Type**. 3D tabletop video
  - **The model capability to evaluate**. object recognition with / without reference
- **Source Data**.
  - rendering images of objects from Objaverse
  - Annotations regarding object category, attribute, and shape
- **Task Plan Schema**.
  - **question type**: `string`. The question type of these tasks will be "what rotate video".
  - **size**: `string`. The type of the size of the target object, indicates whether it pertains to the "largest" or "smallest" in all the objects.
  - **grid number**: `integer`. The number of diagonal grids of the image, N indicates there are $N \times N$ grids in the image. Support $\{2, 3\}$.
  - **target category**: `string`. The category name of the target object.
  - **absolute position**: `string`. The absolute position of the target object in the grid. It is a number ranging from 0 to 3 (grid number = 2) or 0 to 8 (grid number = 3).
  - **attribute type**: `string`. The type of attributes of the target object, currently include: `color`, `material`, and `shape`.
  - **attribute value**: `string`. The value of the attributes of the target object.
- **Partitions**.
  - **Partition 1**.
    - **Template**
      - **Q**: What is the <size> object in the image?
      - **A**: <target category>
    - **Example**
      - **Q**: What is the smallest object in the image?
      - **A**: spatula
- **Limitations**: The current setup is primarily designed for stationary objects and may not effectively assess dynamic scenarios or human actions, such as interactions with objects or motion-based tasks.
- **Recommendations**: A task generator includes compositional and contextual challenges that require deeper reasoning about object relation and recognition.

WhereRotationVideoGridTaskGenerator

- **Basic Information**.
  - **Task Type**. VideoQA
  - **Question Type**. what object
  - **Answer Type**. object category
  - **Image Type**. 3D tabletop video
  - **The model capability to evaluate**. object recognition with / without reference
- **Source Data**.
  - rendering images of objects from Objaverse
  - Annotations regarding object category, attribute, and shape
- **Task Plan Schema**.
  - **question type**: `string`. The question type of these tasks will be "where rotate video".
  - **size**: `string`. The type of the size of the target object, indicates whether it pertains to the "largest" or "smallest" in all the objects.
  - **grid number**: `integer`. The number of diagonal grids of the image, N indicates there are $N \times N$ grids in the image. Support $\{2, 3\}$.
  - **target category**: `string`. The category name of the target object.
  - **absolute position**: `string`. The absolute position of the target object in the grid. It is a number ranging from 0 to 3 (grid number = 2) or 0 to 8 (grid number = 3).
  - **reference category**: `string`. The category name of the object that is used to reference the target object.
  - **reference position**: `string`. The relative position of the target object from the reference object.
  - **attribute type**: `string`. The type of attributes of the target object, currently include: `color`, `material`, and `shape`.
  - **attribute value**: `string`. The value of the attributes of the target object.
  - **target-reference order**: `string`. Define the target object goes first or not in the question. It is related to grammar
- **Partitions**.
  - **Partition 1**.
    - **Template**
      - **Q**: Where is the <size> object in the image?
      - **A**: <absolute position>
    - **Example**
      - **Q**: Where is the largest object in the image?
      - **A**: middle
  - **Partition 2**.
    - **Template**
      - **Q**: Where is the <size> object in the image with respect to the <reference category>?
      - **A**: <reference position>
    - **Example**
      - **Q**: Where is the smallest object in the image with respect to the car?
      - **A**: middle
- **Limitations**: The current setup is primarily designed for stationary objects and may not effectively assess dynamic scenarios or human actions, such as interactions with objects or motion-based tasks.
- **Recommendations**: A task generator includes compositional and contextual challenges that require deeper reasoning about object relation and recognition.

WhatAttributeRotationVideoGridTaaskGenerator

- **Basic Information**.
  - **Task Type**. VideoQA
  - **Question Type**. what object
  - **Answer Type**. object category
  - **Image Type**. 3D tabletop video
  - **The model capability to evaluate**. object recognition with / without reference
- **Source Data**.
  - rendering images of objects from Objaverse
  - Annotations regarding object category, attribute, and shape
- **Task Plan Schema**.
  - **question type**: `string`. The question type of these tasks will be "what attribute rotate video".
  - **size**: `string`. The type of the size of the target object, indicates whether it pertains to the "largest" or "smallest" in all the objects.
  - **grid number**: `integer`. The number of diagonal grids of the image, N indicates there are $N \times N$ grids in the image. Support $\{2, 3\}$.
  - **target category**: `string`. The category name of the target object.
  - **absolute position**: `string`. The absolute position of the target object in the grid. It is a number ranging from 0 to 3 (grid number = 2) or 0 to 8 (grid number = 3).
  - **attribute type**: `string`. The type of attributes of the target object, currently include: `color`, `material`, and `shape`.
  - **attribute value**: `string`. The value of the attributes of the target object.
- **Partitions**.
  - **Partition 1**.
    - **Template**
      - **Q**: What is the <attribute type> of the <size> object in the image?
      - **A**: <attribute value>
    - **Example**
      - **Q**: What is the color of the smallest object in the image?
      - **A**: black
- **Limitations**: The current setup is primarily designed for stationary objects and may not effectively assess dynamic scenarios or human actions, such as interactions with objects or motion-based tasks.
- **Recommendations**: A task generator includes compositional and contextual challenges that require deeper reasoning about object relation and recognition.

WhatObjectSceneGraphTaskGenerator

- **Basic Information**.
  - **Task Type**. ImageQA
  - **Question Type**. what object
  - **Answer Type**. object category
  - **Image Type**. 3D tabletop image
  - **The model capability to evaluate**. object recognition with / without reference
- **Source Data**.
  - rendering images of objects from Objaverse
  - Annotations regarding object category, attribute, and shape
- **Task Plan Schema**.
  - **question type**: `string`. The question type of these tasks will be "what object".
  - **object** : `string`. The target object node of the question.
  - **subgraph** : `string`. The subgraph with the target object node as its root, used to reference the target object node.
  - **scene graph id** : `string`. The identifier of the scene graph.
  - **answers**: `list`. A list of object nodes in the scene graph that share the same subgraph structure, except the target object node and itself.
- **Partitions**.
  - **Partition 1**.
    - **Template**
      - **Q**: What is the <object and its attributes in the subgraph> that <obj reference(other reference objects, attributes, and relations in the subgraph)>?
      - **A**: <target category>
    - **Example**
      - **Q**: What is the flat object that is on the brown and wood table?
      - **A**: paper
- **Limitations**: The current setup is primarily designed for stationary objects and may not effectively assess dynamic scenarios or human actions, such as interactions with objects or motion-based tasks.
- **Recommendations**: A task generator includes compositional and contextual challenges that require deeper reasoning about object relation and recognition.

WhatAttributeSceneGraphTaskGenerator

- **Basic Information**.
  - **Task Type**. ImageQA
  - **Question Type**. what object
  - **Answer Type**. object category
  - **Image Type**. 3D tabletop image
  - **The model capability to evaluate**. object recognition with / without reference
- **Source Data**.
  - rendering images of objects from Objaverse
  - Annotations regarding object category, attribute, and shape
- **Task Plan Schema**.
  - **question type**: `string`. The question type of these tasks will be "what attribute".
  - **attribute type** : `string`. The type of the target attribute.
  - **attribute** : `string`. The target attribute node of the question.
  - **subgraph** : `string`. The subgraph with the target attribute node as its root.
  - **scene graph id** : `string`. The identifier of the scene graph.
  - **answers**: `list`. A list of attribute nodes in the scene graph that share the same subgraph structure, except the target attribute node and itself.
- **Partitions**.
  - **Partition 1**.
    - **Template**
      - **Q**: What is the <attribute type> of the <target attribute's corresponding object and object's other attributes in the subgraph> that <obj reference(other reference objects, attributes, and relations in the subgraph)>?
      - **A**: <attribute>
    - **Example**
      - **Q**: What is the material of the smooth object that is to the right of the yellow container?
      - **A**: plastic
- **Limitations**: The current setup is primarily designed for stationary objects and may not effectively assess dynamic scenarios or human actions, such as interactions with objects or motion-based tasks.
- **Recommendations**: A task generator includes compositional and contextual challenges that require deeper reasoning about object relation and recognition.

WhatRelationSceneGraphTaskGenerator

- **Basic Information**.
  - **Task Type**. ImageQA
  - **Question Type**. what object
  - **Answer Type**. object category
  - **Image Type**. 3D tabletop image
  - **The model capability to evaluate**. object recognition with / without reference
- **Source Data**.
  - rendering images of objects from Objaverse
  - Annotations regarding object category, attribute, and shape
- **Task Plan Schema**.
  - **question type**: `string`. The question type of these tasks will be "what relation".
  - **relation**: `string`. The target relation edge between source object node and target object node
  - **source object**: `string`. The source object node of the question.
  - **target object** : `string`. The target object node of the question.
  - **source subgraph** : `string`. The subgraph with the source object node as its root.
  - **target subgraph** : `string`. The subgraph with the target object node as its root.
  - **scene graph id** : `string`. The identifier of the scene graph.
  - **answers**: `list`. A list of relation edges in the scene graph that connect the same source subgraph and target subgraph.
- **Partitions**.
  - **Partition 1**.
    - **Template**
      - **Q**: What is the relation from the <source object's attributes in the source subgraph> object, which <source obj reference(other reference objects, attributes, and relations in the source subgraph)>, to the <target object's attributes in the source subgraph> object, which <target obj reference(other reference objects, attributes, and relations in the target subgraph)>?
      - **A**: <relation>
    - **Example**
      - **Q**: What is the relation from the standing object, which the colorful and long snowboard is to the right of, to the blue and long object, which is to the left of the patterned skis?
      - **A**: holding
- **Limitations**: The current setup is primarily designed for stationary objects and may not effectively assess dynamic scenarios or human actions, such as interactions with objects or motion-based tasks.
- **Recommendations**: A task generator includes compositional and contextual challenges that require deeper reasoning about object relation and recognition.

WhatObjectVideoSceneGraphTaskGenerator

- **Basic Information**.
  - **Task Type**. VideoQA
  - **Question Type**. what object
  - **Answer Type**. object category
  - **Image Type**. 3D tabletop image
  - **The model capability to evaluate**. object recognition with / without reference
- **Source Data**.
  - rendering images of objects from Objaverse
  - Annotations regarding object category, attribute, and shape
- **Task Plan Schema**.
  - **question type**: `string`. The question type of these tasks will be "what object video".
  - **object** : `string`. The target object the person in the video interacts with.
  - **relation** : `string`. The relation between the person and the target object it interacts with.
  - **reference action** : `string`. The reference action to locate the moment when a person is interacting with the target object.
  - **reference type** : `string`. The target object of the relation between the person and the target object it interacts with, can be "spatial" or "contact"
  - **temporal reference type** : `string`. Type of the temporal reference between the reference action and the moment when a person is interacting with the target object. Can be "before", "while", or "after"
  - **video scene graph id** : `string`. The identifier of the video scene graph.
- **Partitions**.
  - **Partition 1**.
    - **Template**
      - **Q**: What is the object that the person is <reference> <temporal reference type> the person <reference action>?
      - **A**: <object>
    - **Example**
      - **Q**: What is the object that the person is behind after the person watching something in a mirror?
      - **A**: floor
- **Limitations**: The current setup is primarily designed for stationary objects and may not effectively assess dynamic scenarios or human actions, such as interactions with objects or motion-based tasks.
- **Recommendations**: A task generator includes compositional and contextual challenges that require deeper reasoning about object relation and recognition.

WhatRelationVideoSceneGraphTaskGenerator

- **Basic Information**.
  - **Task Type**. VideoQA
  - **Question Type**. what object
  - **Answer Type**. object category
  - **Image Type**. 3D tabletop image
  - **The model capability to evaluate**. object recognition with / without reference
- **Source Data**.
  - rendering images of objects from Objaverse
  - Annotations regarding object category, attribute, and shape
- **Task Plan Schema**.
  - **question type**: `string`. The question type of these tasks will be "what relation video".
  - **object** : `string`. The object the person in the video interacts by the target relation.
  - **relation** : `string`. The target relation between the person and the target object it interacts with.
  - **reference action** : `string`. The reference action to locate the moment when a person is interacting with the object.
  - **reference type** : `string`. The type of the target relation between the person and the object it interacts with, can be "spatial" or "contact"
  - **temporal reference type** : `string`. Type of the temporal reference between the reference action and the moment when a person is interacting with the object. Can be "before", "while", or "after"
  - **video scene graph id** : `string`. The identifier of the video scene graph.
- **Partitions**.
  - **Partition 1**.
    - **Template**
      - **Q**: What is the spatial relation of the person to the <object> while the person <reference action>.
      - **A**: <attribute>
    - **Example**
      - **Q**: What is the spatial relation of the person to the closet while the person closing a closet?
      - **A**: behind
  - **Partition 2**.
    - **Template**
      - **Q**: What is the person doing to the <object> before the person <reference action>?
      - **A**: <attribute>
    - **Example**
      - **Q**: What is the person doing to the blanket before the person putting a phone somewhere?
      - **A**: touching
- **Limitations**: The current setup is primarily designed for stationary objects and may not effectively assess dynamic scenarios or human actions, such as interactions with objects or motion-based tasks.
- **Recommendations**: A task generator includes compositional and contextual challenges that require deeper reasoning about object relation and recognition.

WhatActionVideoSceneGraphTaskGenerator

- **Basic Information**.
  - **Task Type**. VideoQA
  - **Question Type**. what object
  - **Answer Type**. object category
  - **Image Type**. 3D tabletop image
  - **The model capability to evaluate**. object recognition with / without reference
- **Source Data**.
  - rendering images of objects from Objaverse
  - Annotations regarding object category, attribute, and shape
- **Task Plan Schema**.
  - **question type**: `string`. The question type of these tasks will be "what action video".
  - **action** : `string`. The target action that the person in the video performs.
  - **reference action** : `string`. The reference action to locate the moment when a person is performing the target action.
  - **temporal reference type** : `string`. Type of the temporal reference between the reference action and the moment when a person is performing the target action. Can be "before", "while", or "after"
  - **video scene graph id** : `string`. The identifier of the video scene graph.
- **Partitions**.
  - **Partition 1**.
    - **Template**
      - **Q**: What action is the person doing while <reference action>?
      - **A**: <action>
    - **Example**
      - **Q**: What action is the person doing while laughing at something?
      - **A**: sitting at a table
- **Limitations**: The current setup is primarily designed for stationary objects and may not effectively assess dynamic scenarios or human actions, such as interactions with objects or motion-based tasks.
- **Recommendations**: A task generator includes compositional and contextual challenges that require deeper reasoning about object relation and recognition.

References

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