

Scaling Text-Rich Image Understanding via Code-Guided Synthetic Multimodal Data Generation

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Abstract

Reasoning about images with rich text, such as charts and documents, is a critical application of vision-language models (VLMs). However, VLMs often struggle in these domains due to the scarcity of diverse text-rich vision-language data. To address this challenge, we present CoSyn, a framework that leverages the coding capabilities of text-only large language models (LLMs) to automatically create synthetic text-rich multimodal data. Given input text describing a target domain (e.g., “nutrition fact labels”), CoSyn prompts an LLM to generate code (Python, HTML, LaTeX, etc.) for rendering synthetic images. With the underlying code as textual representations of the synthetic images, CoSyn can generate high-quality instruction-tuning data, again relying on a text-only LLM. Using CoSyn, we constructed a dataset comprising 400K images and 2.7M rows of vision-language instruction-tuning data. Comprehensive experiments on seven benchmarks demonstrate that models trained on our synthetic data achieve state-of-the-art performance among competitive open-source models, including Llama 3.2, and surpass proprietary models such as GPT-4V and Gemini 1.5 Flash. Furthermore, CoSyn can produce synthetic pointing data, enabling VLMs to ground information within input images, showcasing its potential for developing multimodal agents capable of acting in real-world environments.

1 Introduction

Instruction-tuned vision-language models (VLMs) have shown strong performance across a range of multimodal tasks (Radford et al., 2021; OpenAI, 2023; Liu et al., 2023). However, these tasks typically focus on general image understanding over natural images rather than the specialized reasoning required for text-rich images such as charts, documents, diagrams, signs, labels, and screenshots. Understanding and reasoning over text-rich

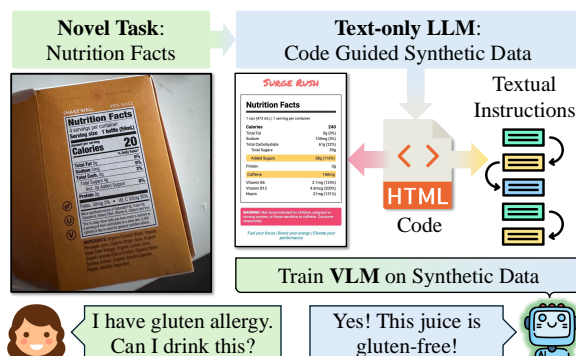


Figure 1: Given a novel task (e.g., answering questions about nutrition facts), our code-guided generation system can produce targeted synthetic data to enhance the performance of VLMs on that specific task.

images is crucial for many applications, including analyzing scientific literature and figures (Asai et al., 2024), improving accessibility for users with visual impairments (Gurari et al., 2018), and enabling agentic workflows in real-world environments (Xie et al., 2024). Effectively interpreting these structured visual formats requires both textual comprehension and spatial reasoning, which current models struggle with due to the limited availability of high-quality, realistic, and diverse vision-language datasets (Methani et al., 2020).

To address these challenges and inspired by the fact that text-rich images are typically rendered from code, we develop **Code Guided Synthetic** data generation system (**CoSyn**), a flexible framework for generating diverse synthetic text-rich multimodal data for vision-language instruction tuning. As illustrated in Figure 2, CoSyn can generate multimodal data for various target domains from a short natural language query, such as *book covers*. CoSyn leverages text-only LLMs, which excel at code generation, to produce both data and code that render diverse text-rich images using 11 supported rendering tools (e.g., Python, HTML, LaTeX). Grounded in the underlying code representation of the images, textual instructions are also

generated by the text-only LLM to create vision-language instruction-tuning datasets.

Using this framework, we construct the CoSyn-400K, as shown in Figure 3, a large-scale and diverse synthetic vision-language instruction-tuning dataset tailored for text-rich image understanding. We comprehensively evaluate the effectiveness of training on CoSyn-generated synthetic data across seven text-rich VQA benchmarks. Our model achieves state-of-the-art performance among competitive open-source models and surpasses proprietary models such as GPT-4V and Gemini 1.5. Notably, training on CoSyn synthetic data enables sample-efficient learning, achieving stronger performance with less data. In addition, CoSyn can synthesize chain-of-thought (CoT) reasoning data (Wei et al., 2022), improving performance on tasks requiring multi-hop reasoning. A fine-grained analysis of question types in ChartQA (Masry et al., 2022) reveals that training on CoSyn-400K results in stronger generalization to human-written questions. In contrast, models trained solely on existing academic datasets often overfit to biased training data, overperforming on templated or machine-generated questions but struggling with more realistic, human-asked queries.

We then identify a key limitation of open-source VLMs that they struggle to generalize to out-of-domain tasks they were not trained on. As shown in Figure 1, we introduce NutritionQA, a novel benchmark for understanding photos of nutrition labels, with practical applications like aiding users with visual impairments. Open-source VLMs perform poorly on this novel task, even after training on millions of images. However, by training on CoSyn-400K, our model adapts strongly to this novel domain in a zero-shot setting with significantly less training data. Remarkably, by generating just 7K in-domain synthetic nutrition label examples using CoSyn for fine-tuning, our model surpasses most open VLMs trained on millions of images. This highlights CoSyn’s data efficiency and ability to help VLMs adapt to new domains through targeted synthetic data generation.

Finally, beyond the standard VQA task, we use CoSyn to generate synthetic *pointing* training data, which is particularly useful in agentic tasks. The pointing data enables VLMs to retrieve coordinates for specific elements in a screenshot given a query like “Point to the Checkout button” (Deitke et al., 2024). Our model trained on synthetic pointing data achieves state-of-the-art performance on the

ScreenSpot click prediction benchmark (Baechler et al., 2024). Overall, our work demonstrates that synthetic data is a promising solution for advancing vision-language models in understanding text-rich images and unlocking their potential as multimodal digital assistants for real-world applications.

2 Related Work

Vision Language Models. Tsimpoukelli et al. (2021) first demonstrate that pre-trained, frozen language models can be extended to process visual inputs. Previous works fuse vision and language modalities using different strategies, such as cross-attention mechanisms (Alayrac et al., 2022) and Q-Former (Li et al., 2023). More recent architectures have converged on using MLP layers to project visual features into the language space (Liu et al., 2023). However, these architectures are often imbalanced, with the language backbone substantially larger than the visual encoder. As a result, without high-quality image-text data, models may overly rely on language priors, leading to hallucinations in their responses (Bai et al., 2024). Our work addresses this issue by generating high-quality multimodal data for text-rich images.

Text-rich Images Understanding. Chart understanding and text-rich image understanding continue to challenge state-of-the-art models as naturally occurring vision-language data that can support training for understanding text-rich images is still scarce (Kahou et al., 2017; Kafle et al., 2018; Xu et al., 2023; Mukhopadhyay et al., 2024). In addition to charts and plots, a number of datasets address other kinds of text-rich images such as documents, infographics, diagrams, and figures, and screenshots (Siegel et al., 2016; Mathew et al., 2021, 2022; Baechler et al., 2024; Roberts et al., 2024) have been made available. Many of these benchmarks are limited in size and scope, diversity of visualization types, and question types, making them suitable for evaluation but not for training data that could lead to generalized performance.

Synthetic Data for VLM. Generating synthetic images with annotations grounded in known source representations has been widely used in domains with limited vision-language data (Johnson-Roberson et al., 2017; Johnson et al., 2017; Cascante-Bonilla et al., 2022; Zhang et al., 2024). This approach has been applied to chart and plot VQA, typically using a limited, small set of chart types and by instantiating handcrafted question

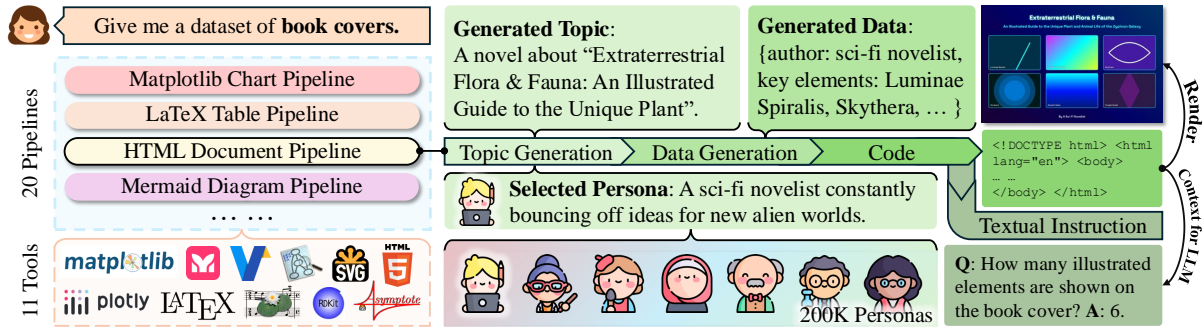


Figure 2: The overview of our **Code Guided Synthetic** data generation system (**CoSyn**), which has 20 generation pipelines based on 11 render tools. Given a user query, e.g., “book cover,” CoSyn selects the appropriate pipelines and starts by generating diverse topics conditioned on personas, then synthesizes detailed data for code generation. The code renders the image and is also fed as context for an LLM to construct instruction-tuning data.

templates (Kahou et al., 2017; Kafle et al., 2018; Methani et al., 2020; Singh and Shekhar, 2020). Following this, Li and Tajbakhsh (2023) and Carbone et al. (2024a) explore using text-only LLMs to generate annotations from tables or text descriptions associated with charts to train VLMs. Other recent approaches, similar to our procedure, explore generating data and code to render synthetic charts (Han et al., 2023; He et al., 2024; Shinoda et al., 2024; Xia et al., 2024). Molmo (Deitke et al., 2024) releases a synthetic text-rich image dataset, **PixMo-docs**, but smaller in scale and diversity than ours. These works generate synthetic data that is still highly limited in terms of the diversity of topics, figure types, and rendering pipelines, which is important for generalizing to out-of-distribution tasks. We expand the scope beyond charts to encompass a wider range of diverse text-rich images.

3 Problem Formulation

Given a text query q about an image type, e.g., *flow charts*, our goal is to create a synthetic multimodal dataset $\mathcal{D}_q = \{(I, T)\}$, where I is the image, and T is the textual instruction-tuning data (e.g., question-answer pairs). \mathcal{D}_q is used to train a VLM to improve its ability to understand images related to q . The core idea of our approach is to use code C as the intermediate representation to bridge the image and text. The overall generation process can be decomposed as follows:

$$P(I, T|q) = P_{\text{LM}}(C|q) \cdot P(I|C) \cdot P_{\text{LM}}(T|C)$$

where $P_{\text{LM}}(C|q)$ represents prompting a language model to generate code C , which is executed to render the image, $P(I|C)$. $P_{\text{LM}}(T|C)$ uses code C (without the image) as context for an LLM to generate the textual instruction-tuning data.

4 CoSyn System

Figure 2 illustrates the workflow of our **Code-Guided Synthetic** data generation system (**CoSyn**). The system takes a language input, such as “generate a dataset of book covers”, and outputs a multimodal dataset. Based on the input query, CoSyn selects one of 20 generation pipelines built on 11 rendering tools. The process starts with topic generation, conditioned on a sampled persona that guides the style and content. Next, the system generates data content and converts it into code, which is then executed to render synthetic images. Finally, using the code as context, we prompt the LLM to generate corresponding textual instructions.

In the following, we provide detailed explanations of the rendering tools supported by CoSyn, the tailored generation pipelines based on these tools, our persona-driven approach to diversifying content and styles, and the large-scale dataset of 400K synthetic images generated by CoSyn.

Rendering Tools. We integrate various rendering tools to generate diverse types of images, forming the foundation of CoSyn’s ability for text-rich image generation. For example, **Matplotlib**, **Plotly**, and **Vega-Lite** are used to create different types of charts. **LaTeX** and **HTML** are used for documents and tables, while **Mermaid** and **Graphviz** generate diagrams. We utilize **SVG** and **Asymptote** to create vector graphics and math-related content. For specialized tasks, we rely on **Lilypond** to generate music sheets and **RDKit** for chemical structures. We implement customized functions for each tool to execute LLM-generated code and obtain corresponding rendered images. These tools collectively enable CoSyn to produce a wide range of high-quality, text-rich synthetic images.

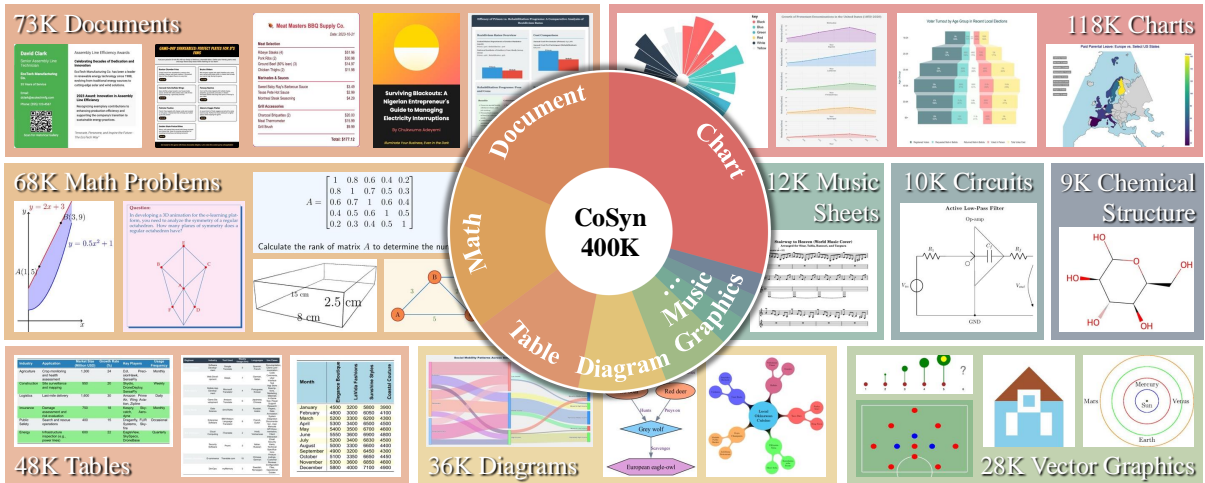


Figure 3: Our CoSyn-400K dataset consists of 9 categories of text-rich images with 2.7M instruction-tuning data. More qualitative examples, along with question-answer annotations, are available in Figure 12 -18 in Appendix C.

Pipelines. We design 20 pipelines based on 11 rendering tools.¹ Each pipeline follows the same procedure: (1) *Topic generation* to define the theme of this synthetic example, (2) *Data generation* to populate the detailed contents, (3) *Code generation* to create executable code that renders the image, and (4) *Instruction generation* conditioned on code to produce instructions, including questions, answers and explanations for chain-of-thought reasoning. Each stage is controlled by a prompt customized for the image category and rendering tool. Figure 9 shows prompts of the HTML Document pipeline.

Use personas to enhance diversity. LLMs often struggle to generate diverse synthetic data using sampling parameters alone (Yu et al., 2023), with biases leading to repetitive outputs across different runs. Recent work (Ge et al., 2024) shows that incorporating personas in prompts can improve diversity by enabling models to generate from varied perspectives. CoSyn adopts personas to enhance diversity during the Topic Generation stage. Each persona is a short sentence describing a personality or identity. For example, as shown in the middle of Figure 2, we sample a persona “a sci-fi novelist who likes alien worlds”, which results in a topic of “a novel about Extraterrestrial Flora & Fauna” for generating the book cover image. We use the 200K personas released by Ge et al. (2024).

Implementation details. CoSyn is built on the DataDreamer library (Patel et al., 2024), which supports robust multi-stage synthetic data generation pipelines that are easy to maintain, reproduce, and extend. DataDreamer documents the prompts

¹Some tools are used in multiple pipelines, e.g., HTML is used for generating documents, tables, and charts.

and parameters used at each generation stage and implements several efficient techniques, such as parallel generation and response caching, to optimize performance. For the data and code generation stages, we use Claude-3.5-Sonnet, which performs well in coding tasks (Anthropic, 2024b). For instruction-tuning data generation, we select GPT-4o-mini (OpenAI, 2023) for its cost efficiency.

CoSyn-400K. As shown in Figure 3, we use CoSyn to generate a large-scale synthetic dataset of 400K images across nine categories: charts, documents, math problems, tables, diagrams, vector graphics, music sheets, electrical circuits, and chemical structures. Since CoSyn is controlled via language inputs, it can easily generate diverse, fine-grained image types by varying the input queries. For instance, we use over 100 queries to generate document data covering *receipts*, *resumes*, *meal plans*, etc. Some queries used for CoSyn-400K are provided in Appendix A.3. This ensures that our dataset covers a broad range of domains. The following sections validate how our synthetic datasets enhance the ability of VLMs to understand text-rich images.

5 Experimental Setup

Our experiments aim to verify the value of our synthetic data in the supervised fine-tuning stage of training vision-language models. This section introduces the architecture of our model, training strategy, datasets we used, baselines for comparison, and other details on implementation.

Model Architecture. We follow the same image preprocessing and architecture as Molmo (Deitke et al., 2024), which uses the MLP layer to con-

Model	ChartQA	DocVQA	InfoVQA	TableVQA	AI2D	TextVQA	ScreenQA	Average
GPT-4V	78.1	87.2	75.1	60.5	89.4	78.0	41.6	72.8
Gemini 1.5 Flash	85.4	89.9	75.3	72.6	91.7	78.7	40.1	76.2
Claude-3 Opus	80.8	89.3	55.6	70.0	88.1	67.5	39.8	70.2
PaliGemma-3B [†]	71.4	84.8	47.8	46.4	73.3	76.5	32.2	61.8
BLIP-3-4B [†]	60.0	61.4	31.5	24.3	74.2	71.0	26.2	49.8
Cambrian-7B [†]	73.3	77.8	41.6	40.6	73.0	71.7	44.4	64.2
LLaVA-1.5-7B ^{†*}	17.8	28.1	25.8	33.1	55.5	58.2	17.6	33.7
LLaVA-Next-8B [†]	69.5	78.2	43.8	43.9	71.6	65.3	34.2	58.1
LLaVA-OneVision-7B [†]	80.0	87.5	<u>68.8</u>	64.6	<u>81.4</u>	<u>78.3</u>	46.3	72.4
Pixtral-12B	81.8	90.7	50.8	67.0	79.0	75.7	39.4	69.2
Llama 3.2 11B	<u>83.4</u>	88.4	63.6	51.1	91.9	73.1	87.7	<u>77.0</u>
Ours (7B) [†]	86.3	<u>90.0</u>	70.5	<u>65.8</u>	91.9	82.0	<u>80.1</u>	80.9
Ours (7B-zero-shot) ^{†*}	80.8	82.9	59.8	64.9	83.9	72.7	78.1	74.7

Table 1: **Results on 7 text-rich benchmarks.** The result of the best-performing open-source model is **bold**, and the second-best is underlined. Models with [†] stand for open data and code for multimodal training. Models with * are zero-shot models, which means the models are not trained on instances from any of the evaluation datasets.

nect the vision encoder and a pretrained LLM. We choose OpenAI’s CLIP (ViT-L/14 336px) (Radford et al., 2021) as the vision backbone and Mistral-7B (Jiang et al., 2023) as the language model.

Training Process. We adopt the same training strategy as Molmo (Deitke et al., 2024), which consists of two stages: (1) *Pre-training* on dense captions from PixMo-Cap and (2) *Supervised fine-tuning* on three categories of datasets below:

- **Evaluation Datasets.** We evaluate our model on seven text-rich benchmarks, including ChartQA (Masry et al., 2022), DocVQA (Mathew et al., 2021), InfographicVQA (Mathew et al., 2022), TableVQA-Bench (Kim et al., 2024), AI2 Diagrams (Kembhavi et al., 2016), TextVQA (Singh et al., 2019), and ScreenQA (Baechler et al., 2024). We adopt their official metrics for calculating performance. In total, we have 138K training images from the evaluation datasets.²
- **Auxiliary Datasets.** We select additional academic datasets for fine-tuning: VQAv2 (Goyal et al., 2017), GQA (Hudson and Manning, 2019), OK-VQA (Marino et al., 2019), OCR-VQA (Mishra et al., 2019), A-OKVQA (Schwenk et al., 2022), ScienceQA (Lu et al., 2022), TabMWP (Lu et al., 2023), ST-VQA (Biten et al., 2019), TallyQA (Acharya et al., 2019), DVQA (Kafle et al., 2018), FigureQA (Kahou et al., 2017), and PlotQA (Methani et al., 2020). The auxiliary datasets contain around 1M training images.
- **Synthetic Datasets.** As introduced in Sec 4 and also shown in Figure 3, our synthetic datasets include 400K text-rich images from 9 categories.

²TableVQA is an eval-only benchmark (no training split), and we do not use the training split from ScreenQA.

Our best-performing model uses all three categories of datasets above. We also trained a zero-shot model using only auxiliary and synthetic data without any examples from the evaluation datasets, which still exhibits competitive benchmark performance, as shown in the last row of Table 1.

Baselines. We compare recent open-source VLMs with a similar scale (7B), including PaliGemma-3B (Beyer et al., 2024), BLIP-3-4B (Xue et al., 2024), Cambrian-7B (Tong et al., 2024), LLaVA-1.5-7B (Liu et al., 2023), LLaVA-Next-8B (Liu et al., 2024), LLaVA OneVision-7B (Li et al., 2024), Pixtral-12B (Agrawal et al., 2024), Llama 3.2 V (Meta, 2024). We also include proprietary models: GPT-4V (OpenAI, 2023), Gemini-1.5-Flash (Team, 2024), and Claude-3 Opus (Anthropic, 2024a).

Implementation Details. We train our model on TPU v3-128 with a batch size of 32. Our best-performing model is trained for 60K steps, taking about 30 hours. The checkpoints with the highest validation performance are retained for testing.

6 Results

This section covers (1) the competitive performance of the model trained on our synthetic data (Sec 6.1), (2) the comprehensive analyses to highlight the benefits of synthetic data (Sec 6.2), and (3) the effectiveness of synthetic pointing data in improving VLMs for web agent tasks (Sec 6.3).

6.1 Main Results

Table 1 compares our model’s performance with both open and closed models across seven text-rich benchmarks. On average, our 7B model achieves

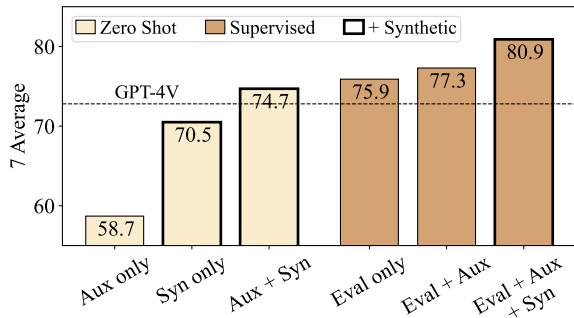


Figure 4: **Ablation on training data selection.** Aux, Syn, and Eval stand for auxiliary, synthetic, and evaluation datasets, respectively. We report the average score on seven benchmarks. The detailed performance breakdown on each benchmark is in Table 8.

the highest performance, surpassing the second-best model (Llama 3.2 11B) by 3.9%. Notably, our model ranks first in four out of the seven datasets and second in the remaining three. More surprisingly, our zero-shot model (the last row in Table 1) outperforms most open and closed models without exposure to any training instances from the evaluation datasets. In contrast, these competing models often rely on benchmark training data and are thus not true zero-shot models. This result demonstrates that the capabilities learned from our synthetic data can transfer effectively to downstream tasks.

6.2 Analysis

In the following experiments, we quantify the contribution of synthetic data to the benchmark performance by ablating the combinations of fine-tuning datasets. Then, we demonstrate that our CoSyn system can efficiently assist VLMs in generalizing to novel tasks. Finally, we show that synthetic data can help mitigate the overfitting of biases.

Synthetic data boosts the performance. Figure 4 presents an ablation study on the choices of supervised fine-tuning data. In the zero-shot settings, when the model is trained on auxiliary datasets (over 1M training images not directly from the evaluation tasks), it fails to generalize effectively to the evaluation tasks, with a substantial performance gap of 14.1% below GPT-4V. However, using only 400K synthetic samples achieves a performance comparable to GPT-4V. Our best zero-shot model surpasses GPT-4V when jointly training synthetic and auxiliary data. Under the supervised settings, training with in-domain data alone yields strong performance. However, adding 1M auxiliary samples provides a modest improvement of 1.4%, while incorporating synthetic data results in a more

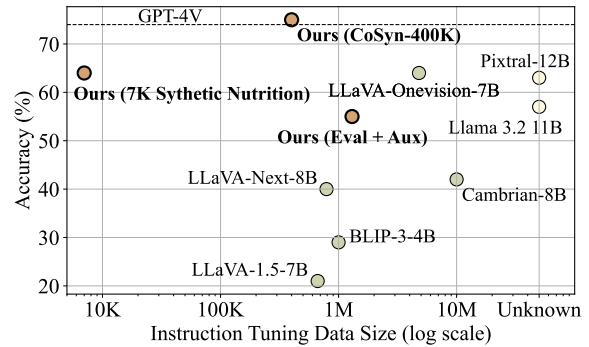


Figure 5: **Zero shot performance on NutritionQA.** The x-axis denotes the number of training examples used for the instruction-tuning stage. The models on the upper left side demonstrate better data efficiency.

significant 3.6% boost. These results demonstrate the effectiveness of synthetic data in enhancing VLMs’ performance on text-rich tasks.

Zero-shot Generalization on a Novel Task.

Vision-language models typically rely on in-domain data to perform well on specific tasks. When encountering a novel task, such as answering questions about nutrition labels in Figure 1, models without seeing similar examples during training may struggle with this novel task. However, our CoSyn system enables controllable data generation. Given the task name as input, CoSyn can generate task-specific data to fine-tune the model.

To validate this, we annotated a small evaluation dataset called **NutritionQA**, which includes 100 examples of questions about photos of nutrition labels. Some questions require multi-hop reasoning, as Figure 10 illustrates. We evaluated GPT-4V and several open-source VLMs on this dataset and report the performance in Figure 5. The x-axis in Figure 5 represents the amount of data used during the instruction fine-tuning stage.

Despite being trained on millions of images, we observe that open-source VLMs are not data-efficient and perform poorly on this novel task compared to GPT-4V. Although many open-source VLMs claim to achieve GPT-4V-level performance, they fall short when tested on new tasks in the wild. Without synthetic data, our model (Eval + Aux) achieves results similar to those of open models. However, when trained on 400K synthetic samples, our model matches GPT-4V’s performance.

More impressively, we used CoSyn to generate 7K synthetic nutrition label samples and fine-tuned the model using only this 7K data. The resulting model outperforms most open-source VLMs on the NutritionQA task. These results demonstrate that

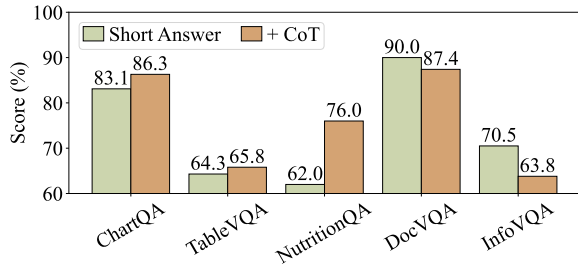


Figure 6: **Ablation of using Chain-of-Thought reasoning.** Short Answer represents prompting model to output the answer as short as possible. + CoT stands for providing Chain-of-Thought reasoning before giving the final answer. Results on all datasets are in Table 7.

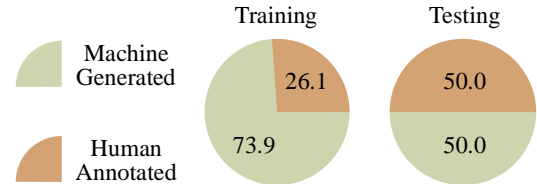
code-guided synthetic data is an effective and efficient method for adapting VLMs to new domains.

Synthetic Data for Chain-of-Thought Reasoning. Existing text-rich datasets, such as ChartQA (Masry et al., 2022), are typically annotated with short answers. However, questions like “Compute the mean of the data in the plot” require step-by-step mathematical reasoning to arrive at the correct answer. Models trained only with short-answer supervision may fail to learn proper plot comprehension, but instead overfit to annotation biases in these datasets. On the contrary, our CoSyn-400K includes explanation text alongside the short answer. Each instruction-tuning example consists of a (*question, explanation, short answer*) triplet, enabling models to learn chain-of-thought (CoT) reasoning. During fine-tuning, we design two prompt templates for our synthetic data:

CoT Prompt: <Question> Provide reasoning steps and then give the short answer.
<Explanation> Answer: <Answer>

Short Answer Prompt: <Question> Answer with as few words as possible. <Answer>

Those prompts allow VLMs to switch between the two answering styles and perform CoT reasoning when necessary. Figure 6 shows that incorporating CoT reasoning improves performance on ChartQA, TableVQA, and NutritionQA, as these datasets contain examples requiring multi-hop reasoning. However, we observe that adding CoT reasoning reduces performance on DocVQA and InfoVQA. We find that answer biases in these benchmarks cause this decline. Specifically, the ground-truth answers favor short responses, often penalizing more detailed and verbal responses. For instance, in DocVQA, the ground-truth for an ex-



ChartQA	Average	Machine	Human	Δ ↓
PaliGemma-3B	71.4	88.5	54.2	34.3
ChartPali-5B	77.3	93.7	60.9	32.8
Ours (w/o Syn)	81.4	92.2	70.4	21.8
Ours (w/ Syn)	86.3	93.4	79.1	14.2

Table 2: **Results on human and machine-generated questions of ChartQA.** The pie charts above display the percentage distribution of two question types in training and testing. Δ (\downarrow lower is better) denotes the performance gap between human and machine questions.

ample is “T-Th”, whereas the model responds with “Tuesday to Thursday”. Although the response is correct, the strict string-matching metric assigns it a zero score. This highlights key limitations of current multimodal benchmarks, including answering biases and rigid evaluation metrics that fail to capture the full extent of a model’s capabilities.

Synthetic Data for Mitigating Biases. Our previous experiments reveal answering biases in multimodal benchmarks, which VLMs trained solely on these datasets often inherit. To further validate this issue, we analyze ChartQA and observe a distribution shift in question types. As shown in the pie charts above Table 2, some ChartQA questions are human-annotated, while others are generated by the language model T5 (Raffel et al., 2020), which is heavily influenced by prompt phrasing and limited to a fixed set of question templates. During training, most questions (73.9%) in ChartQA are machine-generated, while the test set contains an even distribution of human-annotated and machine-generated questions. Models trained exclusively on ChartQA tend to overfit to T5-generated questions. Table 2 illustrates this issue: PaliGemma (Beyer et al., 2024) and ChartPali (Carbone et al., 2024b) achieve high accuracy on machine-generated questions but experience a significant performance drop of over 30% on human-annotated questions.

Similarly, without synthetic data, our model shows a noticeable 21.8% gap between the two question types. However, incorporating synthetic data during training reduces this gap to 14.2%. This suggests that synthetic data can mitigate overfitting on benchmarks and enhance VLMs’ usability in real-world human-asked questions.

Dataset	Image Diversity	Text Diversity
FigureQA	0.268	0.567
DVQA	0.307	0.752
PlotQA	0.420	0.743
ChartQA	0.340	0.742
Ours (Charts)	0.596	0.823

Table 3: **Compare image and text diversity across different chart datasets.** We randomly sample 10K instances from each dataset to compute the results.

n. of Tools	Diversity	ChartQA		
		Average	Machine	Human
SINGLE	0.572	73.9	66.5	81.5
MULTIPLE	0.607	75.2	68.6	82.0

Table 4: **Single vs. Multiple Rendering Tools for Data Generation.** Each row uses the same number of 45K synthetic images. SINGLE only uses Matplotlib, while MULTIPLE involves four other rendering tools: HTML, LaTeX, Plotly, and VegaLite.

Our synthetic data is more diverse. To quantify the diversity of images and text in our synthetic dataset $\mathcal{D} = \{(I, T)\}$, we propose the following two metrics to compute the diversity:

$$\text{Diversity}(\mathcal{D})_{\text{Image}} = \frac{1}{|\mathcal{D}|^2 - |\mathcal{D}|} \sum_{I_i \in \mathcal{D}} \sum_{I_j \in \mathcal{D}}^{i \neq j} (1 - \text{sim}(I_i, I_j))$$

$$\text{Diversity}(\mathcal{D})_{\text{Text}} = \frac{1}{|\mathcal{D}|^2 - |\mathcal{D}|} \sum_{T_i \in \mathcal{D}} \sum_{T_j \in \mathcal{D}}^{i \neq j} (1 - \text{sim}(T_i, T_j))$$

where $\text{sim}(\cdot)$ is the cosine similarity function. Both metrics compute the average pairwise cosine distance between the features of every instance in the dataset. For image diversity, we extract features using CLIP, while for text diversity, we use Sentence-BERT (Reimers, 2019) to obtain embeddings of question-answer pairs. Table 3 shows that our synthetic charts are significantly more diverse than those in existing datasets, such as FigureQA and ChartQA, in both image and text diversity.

Diversity correlates with model performance. We observe that data diversity significantly affects model performance on downstream tasks. To investigate this, we compare synthetic chart data generated using only a single tool (Matplotlib) with charts generated by all five tools available in our CoSyn system. As shown in Table 4, using multiple tools results in higher image diversity and notably improved performance on ChartQA. This experiment underscores the importance of data diversity for enhancing the generalizability of models.

Scaling the size of synthetic data. In addition to diversity, the scale of synthetic data also impacts model performance. As shown in Figure 7,

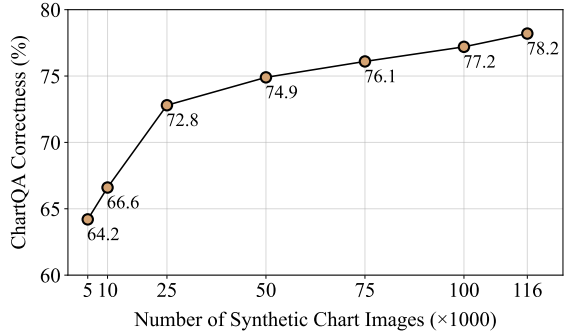


Figure 7: **Scaling the Size of Synthetic Data.** We evaluate the *zero-shot* performance on ChartQA of models fine-tuned on increasing numbers of synthetic images.

LLM for Data Generation	ChartQA		
	Average	Machine	Human
GPT-4o	72.4	65.8	78.9
Claude-3.5-sonnet	77.2	71.0	83.8

Table 5: **Compare the LLMs used for synthetic data generation.** For both LLMs, we create 100K synthetic charts for fine-tuning the VLMs. We report the *zero-shot* evaluation results on ChartQA.

increasing the number of synthetic chart images leads to improved performance on ChartQA. This demonstrates that scaling up synthetic data can further enhance VLMs on downstream tasks. Due to resource constraints, our final dataset consists of 400K images, which cost us about \$8,000. Future work could explore scaling up the dataset size to push the boundaries of synthetic data’s potential.

Compare LLMs for synthetic data generation. In the default setting, CoSyn uses Claude-3.5-sonnet as the underlying LLM for code generation. To highlight the importance of strong coding capabilities, we compare it with data generated by GPT-4o. As shown in Table 5, synthetic data generated by Claude-3.5-sonnet yields significantly better results than GPT-4o. Our qualitative observation reveals that GPT-4o has a higher failure rate in code generation, particularly for less common coding languages or libraries. This result emphasizes that a strong LLM is essential for the successful synthetic data generation for VLMs.

6.3 Synthetic Pointing Data

Pointing enables VLMs to answer questions by providing specific points on images. This allows models to ground their responses in visual content and interact with environments, which is crucial for developing digital agents. We find that our code-guided system can synthesize pointing data.

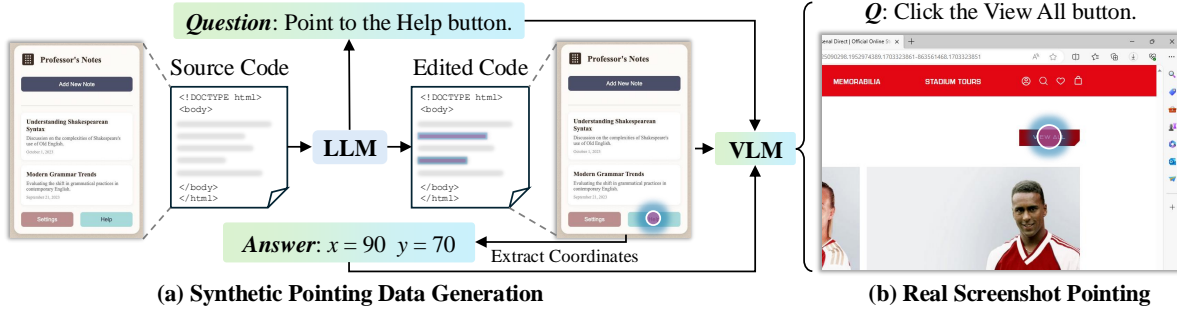


Figure 8: **The overview of enabling VLMs to point through synthetic data.** (a) We synthesize pointing data by prompting an LLM to generate pointing questions and edit the code to draw the answer points explicitly. (b) We demonstrate that the VLM trained on synthetic pointing data can be generalized to real agentic tasks.

Method. Since we have access to the source code for all generated images, we can prompt an LLM to modify the code to draw points on the images explicitly. As illustrated in Figure 8, we feed the image’s source code as context to the LLM, which generates a pointing question and edits the code to draw points with a predefined color. By extracting the pixel values of these points, we can obtain their exact (x, y) coordinates.³ We then use this pointing data to train VLMs, enabling them to answer questions by providing point coordinates. In total, we generate pointing data for 65K synthetic images. Figure 19 shows some qualitative examples from our synthetic pointing dataset.

Setup. We evaluate pointing ability on ScreenSpot (Cheng et al., 2024), where the task requires models to provide the correct click location based on a given instruction. ScreenSpot contains screenshots from mobile phones, desktops, and web pages. To assess the effectiveness of our synthetic pointing data, we compare it to the model trained on PixMo-point (Deitke et al., 2024), which consists of 155K human-annotated images. Our best-performing model uses both PixMo-point and synthetic pointing data. Additionally, we compare against existing methods like CogAgent (Hong et al., 2024), SeeClick (Cheng et al., 2024), and UGround (Gou et al., 2024), which is trained on 1.3M screenshots.

Results. Table 6 compares the click accuracy of our models with previous methods. Using 65K synthetic pointing samples, our model achieves performance comparable to that trained on 155K human-annotated samples. When combining synthetic and human data, our model achieves state-of-the-art performance on ScreenSpot, surpassing the recent UGround (Gou et al., 2024), which was trained on

³The coordinates of points are normalized to (0, 100) to mitigate the influence of image resolution.

Model	Mobile		Desktop		Web		Avg
	Text	Icon	Text	Icon	Text	Icon	
GPT-4o	20.2	24.9	21.1	23.6	12.2	7.8	18.3
CogAgent	67.0	24.0	74.2	20.0	70.4	28.6	47.4
SeeClick	78.0	52.0	72.2	30.0	55.7	32.5	53.4
UGround	82.8	<u>60.3</u>	82.5	<u>63.6</u>	80.4	70.4	<u>73.3</u>
Synthetic	90.8	53.3	78.4	58.6	80.0	47.1	68.0
Human	84.2	59.0	88.1	52.9	76.5	50.5	68.5
Combined	89.0	65.1	87.6	65.7	83.0	<u>58.7</u>	74.9

Table 6: **Click accuracy on ScreenSpot.** We report our models trained on different pointing data. Human stands for using the human-annotated data from PixMo-point (Deitke et al., 2024). Combined means combining human-annotated data with our synthetic pointing data.

1.3M screenshots. These results demonstrate that synthetic pointing data is a data-efficient approach for improving VLM performance on agentic tasks involving click prediction.

7 Conclusion

In this work, we introduced CoSyn, a framework for generating synthetic data that significantly enhances VLM performance on text-rich image understanding. Our comprehensive analysis highlights the advantages of synthetic data for domain generalization, data efficiency, and bias mitigation. Our work demonstrates that the coding capabilities of text-only LLMs can effectively assist multi-modal learning and unleash the potential of vision-language models for real-world applications.

Limitation

The effectiveness of synthetic data depends heavily on the quality and diversity of the prompts and rendering pipelines used for data generation. For highly specialized or underrepresented domains, generating sufficiently diverse data remains chal-

lenging and may require careful prompt engineering or additional customization of rendering tools. Targeted synthetic data generation may be essential for certain tasks to achieve adequate performance, and ensuring relevance and coverage still requires domain-specific expertise. Synthetic data also may not fully capture the complexity of real-world data in some scenarios. Therefore, improving the diversity and realism of synthetic data to better support models in highly variable or evolving domains is a reasonable avenue for future research. Finally, our current synthetic data is limited to English and may require further extension for multilingual support.

Ethical Statement

To the best of our knowledge, this work presents no significant ethical concerns. We note, however, that the use of synthetic data can propagate biases present in the generation model used. Conversely, synthetic data can also help mitigate biases and expand coverage, as demonstrated in this work, by greatly expanding the domains present in vision-language instruction-tuning training data to yield stronger generalized performance.

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A Implementation Details

A.1 Prompts

We provide the prompt templates in Figure 9 for the *HTMLDocumentPipeline* as an example to illustrate the prompts used across our code-guided synthetic data generation pipelines.

Topic Generation: You are an expert in document generation and have a broad knowledge of different topics. My persona is: "**PERSONA**" I want you to generate **NUM_TOPICS** topics for **FIGURE_TYPE** that I will be interested in or I may see during my daily life given my persona. Here are the requirements:

1. Each topic is a high-level summary of the contents in **FIGURE_TYPE** with some design details, e.g., "the utility bill for the month of January 2022 with a detailed breakdown of charges".
2. The topics should be diverse to help me generate varied documents. Each topic should be unique and not overlap with others.
3. The topics are conditioned on the document type. Please ensure the topics you provided can be best visualized in "**FIGURE_TYPE**".
4. All topics must be in English, even if the persona is non-English.
5. List **NUM_TOPICS** topics for "**PERSONA**" and separate them with a | character, e.g., topic1 | topic2 | | topicN.

Do not include any additional text at the beginning or end of your response.

Data Generation: You are an expert in content creation and have broad knowledge about various topics. My persona is: "**PERSONA**" I need some materials about "**TOPIC**", which can be used to generate a **FIGURE_TYPE**. Here are the requirements:

1. The materials should be related to the topic and customized according to my persona. Its structure must be suitable for the **FIGURE_TYPE**.
2. The materials should be realistic, and the contents should be named using real-world entities. Do not use placeholder names like xxA, xxB, etc. Do not use template data like [Name], [Date], etc.
3. The materials should be diverse and contain information from different aspects of the topic to ensure the document is informative.
4. Do not provide too many materials. Just provide key pieces of information that are essential for a **one-page document**.
5. All materials must be in English, even if the persona is non-English.

Please provide the materials in JSON format without additional text at the beginning or end.

Code Generation: You are an expert web designer and are good at writing HTML to create documents. My persona is: "**PERSONA**" I have some materials about **TOPIC** which can be used to generate a **FIGURE_TYPE**. Here are the materials (JSON format):
<data> **DATA** </data>
Please use HTML and CSS to generate a **FIGURE_TYPE** using the data provided. Here are the requirements:

1. **Style Requirements:** Feel free to use any CSS framework, libraries, JavaScript plugins, or other tools to create the document.
 - (1) Try to be creative and make the web page style, fonts, colors, borders and visual layout unique with CSS. Taking persona, topic, and document type into consideration when designing the document.
 - (2) Select the appropriate design scale (e.g., margins, page size, layout, etc) to ensure the information in the document is clear and easy to understand, with no text overlapping, etc.
 - (3) **Do not make the page too long or too sparse.** All contents should be in **one page**. This is very important.
2. **Code Requirements:**
 - (1) You need to hardcode the provided data into the HTML script to generate the document. Be careful with the syntax and formatting of the HTML.
 - (2) Put everything in one HTML file. Do not use external CSS or JavaScript files.
 3. **Output Requirements:** Put `<html` at the beginning and `</html` at the end of the script to separate the code from the text. Please don't answer with any additional text in the script, your whole response should be the HTML code which can be directly executed.

Instruction Generation: You are an expert in data analysis and good at asking questions about documents. My persona is: "persona" I want you to generate some question-answer pairs of a **FIGURE_TYPE** about **TOPIC**, which I would ask. Instead of showing the document, I provide the data and the code that generates the document.
<data> **DATA** </data> <code> **CODE** </code>
Please come up with a list of **reasonable questions** that people will ask when they see the rendered document. Here are the requirements:

1. **Question Types:** All questions should be short-answer questions that are answerable based on the visual information in the document. All questions can be answered with a single word, phrase, or number. (as short as possible)
 - (1) **Information Retrieval questions** ask for specific information in the document, such as numbers, names, dates, titles, etc. The questions should cover different aspects (areas) of the document. This is the most common type of question.
 - (2) **Reasoning questions** require reasoning over multiple information in the document. These questions should be more challenging and require a deeper understanding of the document.
 - (3) **Document Type-specific questions** are questions that are specific and unique to this document type **FIGURE_TYPE**. These questions should be tailored to the content and structure of the document.
2. **Response Format:** Use | to separate the question, explanation, and concise answer for each example.
 - (1) Follow this format: question | explanation | concise answer, e.g., what is the total revenue? | The total revenue is the sum of all revenue sources in the document, which is \$2000 + \$3000 + \$5000 = \$10000. | \$10000
 - (2) Separate the question-answer pairs by double newlines. question1 | explanation1 | answer1
question2 | explanation2 | answer2...
 - (3) Do not provide too many questions, 5-10 questions are enough. Focus on the diversity and quality of the questions. Try to cover different aspects of the document.
 - (4) The concise answer should be as short as possible and directly answer the question. The answer should be faithful and exactly the same as what you would expect to see in the document, don't rephrase it. All words in the answer should be processed in natural language, no coding terms/characters.

Please follow the format strictly and do not include any additional text at the beginning or end of your response.

Figure 9: Prompt templates used for HTML Document Pipeline, including all four stages of generation: topic, data, code, and instruction.

A.2 Rendering Tools and Pipelines

We design 20 generation pipelines built on 11 rendering tools to support the creation of nine categories of text-rich images: (1) **Charts:** Matplotlib VegaLite, Plotly, LaTeX, HTML; (2) **Documents:** LaTeX, HTML; (3) **Tables:** LaTeX, Matplotlib, Plotly, HTML; (4) **Diagrams:** Graphviz, LaTeX, Mermaid; (5) **Math Problems:** LaTeX; (6) **Vector Graphics:** SVG, Asymptote; (7) **Music Sheets:** LilyPond; (8) **Electrical Circuits:** LaTeX; (9) **Chemical Structures:** Rdkit. In addition, we implement a separate pipeline for generating pointing data using HTML as the rendering tool.

A.3 Queries to Construct CoSyn-400K

Since CoSyn accepts textual queries to control data generation, we use a diverse set of queries for each type of text-rich image to ensure broad domain coverage. Below are some examples of the queries used to generate CoSyn-400K:

- **Charts:** Bar, Line, Pie, Diverge bar, Bubble, Scatter, Histogram, Area, Box plot, Heatmap, Error bar, Radar chart, Rose chart, Stem plot, Stairs plot, Violin chart, 2D contour, Distplots, Log plot, Ternary plots/contour, Candlestick charts, Time series, etc. (51 queries in total)
- **Documents:** Letter, Form, Report, Receipt, Invoice, Restaurant menu, Newsletter, Schedule, Manual, Brochure, Transaction document, Agenda, Memo, Financial report, Telephone records, Note, Budget, Meeting minutes, Bill, Catalog, Email, Fax, Policy document, Resume, Infographics, Process infographic, Statistical infographic, etc. (107 queries in total)
- **Math Problems:** Algebra, Counting, Probability, Geometry, Number theory, Precalculus, Prealgebra, Intermediate Algebra, Statistics, Functions, Complex numbers, Logarithms, Inequalities, Linear equations, Exponents, Series, College Algebra, Calculus, Advanced calculus, Linear algebra, Solid geometry, Analytic geometry, Polynomial arithmetic, etc. (110 queries in total)
- **Tables:** Financial table, Simple table, Pivot table, Comparison table, Timeline table, Decision table, Truth table, Lookup table, Periodic table, Statistical table, Timetable, Hierarchical table, Matrix table, Contingency table, Logarithmic table, Correlation table, etc. (35 queries in total)
- **Diagrams:** Flow chart, Directed graph, Undirected graph, Decision tree, Mind map, Gantt charts, Finite state machine, Quadrant chart, Chord diagrams, Network diagrams, Sankey diagram, Entity relationship diagram, Sequence diagrams, Bottom-up flow chart, Timeline, State diagram, Concept map, Family tree, Programming flowchart, etc. (34 queries in total)
- **Vector Graphics:** Visual intelligence test, Spatial intelligence test, Geometry, Solid geometry, Analytic geometry, Polynomial graphs, Trigonometry, Polar coordinates, Coordinate system, Topology, Graph theory, Plane geometry, Functions, Calculus, Vectors, Angles, Perimeter and area problems, etc. (36 queries in total)
- **Sheet Music:** Classical, Pop, Rock, Jazz, Blues, Hip Hop, Rap, Electronic, Country, Folk, Rhythm and blues, Soul, Reggae, Metal, Punk, Theme, Dance, etc. (34 queries in total)
- **Electrical Circuits:** Series, Parallel, Hybrid, Household appliances, Industrial appliances, Mobile device, Low-power appliances, High-power appliances, etc. (30 queries in total)
- **Chemical Structures:** Drug, Organic, Inor-

ganic, Protein, Acids, Bases, Gases, Liquids, Solids, Oxidizers, Flammable liquids, Toxic chemicals, Hazardous chemicals, Aromatic compounds, Aliphatic compounds, Polymers, Metals, Alloys, Electrolytes, etc. (100 queries in total)

A.4 Academic Datasets

During the supervised fine-tuning stage, we include academic datasets in addition to our synthetic datasets. Below, we provide details on the size of these datasets and the evaluation metrics used.

Dataset Size. The number in parentheses indicates the number of training images for each dataset: ChartQA (28.3K), DocVQA (39.5K), InfographicVQA (23.9K), AI2 Diagrams (11.4K), TextVQA (34.6K), VQAv2 (82.8K), GQA (72.1K), OK-VQA (9.0K), OCR-VQA (166.0K), A-OKVQA (17.1K), ScienceQA (6.2K), TabMWP (23.1K), ST-VQA (18.9K), TallyQA (133.0K), DVQA (200.0K), FigureQA (100.0K), PlotQA (160.0K). We downsample some very large synthetic datasets, such as DVQA, FigureQA, and PlotQA, to balance the dataset size. In total, we use approximately 1.1M images from academic datasets.

Evaluation Metrics. We adopt their official evaluation metrics for the seven text-rich datasets. For ChartQA, we use relaxed correctness, which allows a 5% difference for float number answers. For DocQA and InfoQA, we report Average Normalized Levenshtein Similarity (ANLS). For TableVQA, we report the average performance across the four subsets (VTabFact, VWTQ, VWTQ-Syn, FinTabNetQA) using the metrics provided in this [repo](#). We report the multiple choice accuracy for AI2D, VQA score (Goyal et al., 2017) for TextVQA, and SQuAD F1 score (Rajpurkar et al., 2018) for ScreenQA.

A.5 Training Details

Image Preprocessing. We adopt the same image preprocessing as Molmo (Deitke et al., 2024), where each input image is cropped into multiple overlapping crops before being encoded by CLIP. During training, we limit the maximum number of crops to 12, but we increase it to 25 at testing time to accommodate the high resolution of text-rich images. This strategy boosts the inference performance without increasing training costs.

Hyper Parameters. We set the maximum sequence length for training to 2304 tokens. We use the same learning rate of 1e-6 for the MLP con-

Prompt Type	ChartQA	DocVQA	InfoVQA	TableVQA	AI2D	TextVQA	ScreenQA	NutritionQA
CoT	86.3	87.4	63.8	65.8	86.0	70.9	79.0	76.0
Short Answer	83.1	90.0	70.5	64.3	91.9	82.0	80.1	62.0

Table 7: **Ablation of using chain-of-thought (CoT) in prompts.** CoT means letting the model provide reasoning steps before giving the final answer. Short Answer prompts the model to answer with as few words as possible.

FT Data	ChartQA	DocVQA	InfoVQA	TableVQA [†]	AI2D	TextVQA	ScreenQA [†]	Average
Aux only*	60.7	56.2	39.7	43.1	81.7	68.5	61.3	58.7
Syn only*	79.4	80.5	60.1	64.4	68.6	63.6	76.6	70.5
Aux + Syn*	80.8	82.9	59.8	64.9	83.9	72.7	78.1	74.7
Eval only	77.4	87.4	63.8	51.8	91.3	81.1	78.1	75.9
Eval + Aux	81.4	87.9	68.2	53.6	91.6	81.8	77.0	77.3
Eval + Aux + Syn	86.3	90.0	70.5	65.8	91.9	82.0	80.1	80.9

Table 8: **Ablation of the data selection for supervised fine-tuning.** Aux, Syn, and Eval stand for auxiliary, synthetic, and evaluation datasets, respectively. The rows with * represent zero-shot models (without using any training examples from any of the evaluation datasets). The datasets with [†] are test-only datasets (no training splits), which means all numbers on these datasets are zero-shot performance.

neator, LLM, and visual encoder, with batch size 32. The best-performing model is trained for 60K steps with 200 warm-up steps and a cosine scheduler with an end factor of 0.1. All experiments are run on a single TPU v3-128.

B Additional Analysis

We conduct additional analyses below to investigate further why our synthetic data can effectively enhance vision-language models.

Quantify the contributions of synthetic data. Table 8 presents the performance across benchmarks using different combinations of supervised fine-tuning data. A clear trend shows that synthetic data significantly contributes in both zero-shot and supervised settings. Adding our synthetic data consistently boosts performance on each benchmark.

The impact of Chain-of-thought reasoning. We compare the performance of CoT and short-answer prompts in Table 7. CoT reasoning improves performance on ChartQA, TableVQA, and NutritionQA, where questions require multi-hop and mathematical reasoning that aligns with the findings in language tasks (Sprague et al., 2024). However, short-answer prompts yield better results for the other five datasets due to their annotation biases favoring concise responses. CoT responses tend to be more verbose, which may not match the ground-truth answers exactly, resulting in a performance drop.

Document Pointing Task. To further validate the effectiveness of our synthetic pointing data, we introduce DocPointQA⁴, a new pointing task

with 300 question-point pairs annotated from the DocVQA validation set (Figure 11). We compare models trained on human-annotated PixMo-point data (155K examples), our synthetic pointing data (65K examples), and their combination. Since DocPointQA requires multiple-point answers, we report precision, recall, F1 score, and L2 distance (lower is better) after mapping predicted points to ground truth, following the same setup as Molmo (Deitke et al., 2024). As shown in Table 9, the model trained on our synthetic data outperforms the one trained on PixMo-point. Performance improves even further when both datasets are combined, demonstrating the effectiveness of synthetic data in enhancing the pointing capabilities of vision-language models.

Pointing Data	Precision	Recall	F1	Distance ↓
PixMo-point	49.7	49.3	52.7	17.3
Synthetic (Ours)	63.8	66.1	62.8	9.2
Combined (Ours)	69.9	70.6	70.7	8.8

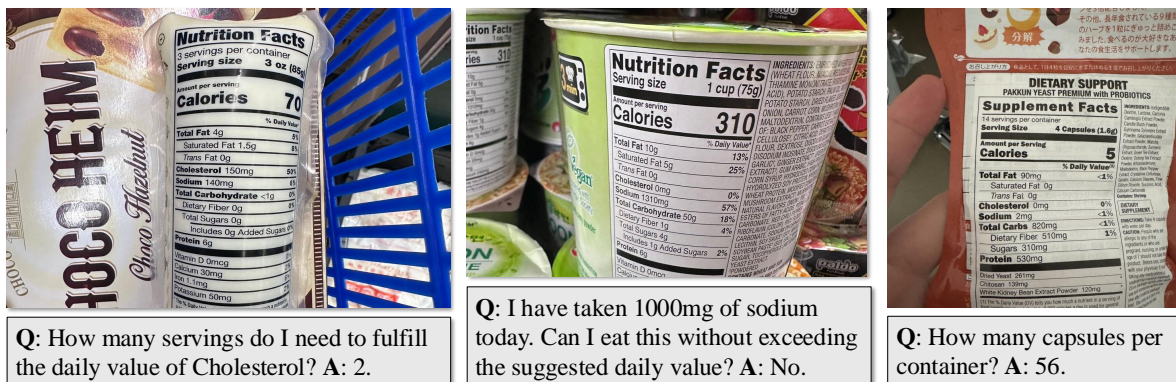
Table 9: **Zero-shot Pointing on DocPointQA.** We compare the models trained on different pointing data. Combined stands for combining PixMo-point (human-annotated) (Deitke et al., 2024) with our synthetic data.

C Qualitative Examples

Figure 10 and 11 show the examples from our annotated NutritionQA⁵ and DocPointQA. Figures 12 - 18 list examples from the 9 categories of synthetic text-rich images. Figure 19 illustrates examples from the synthetic pointing dataset.

⁴<https://huggingface.co/datasets/yyupenn/DocPointQA>

⁵<https://huggingface.co/datasets/yyupenn/NutritionQA>

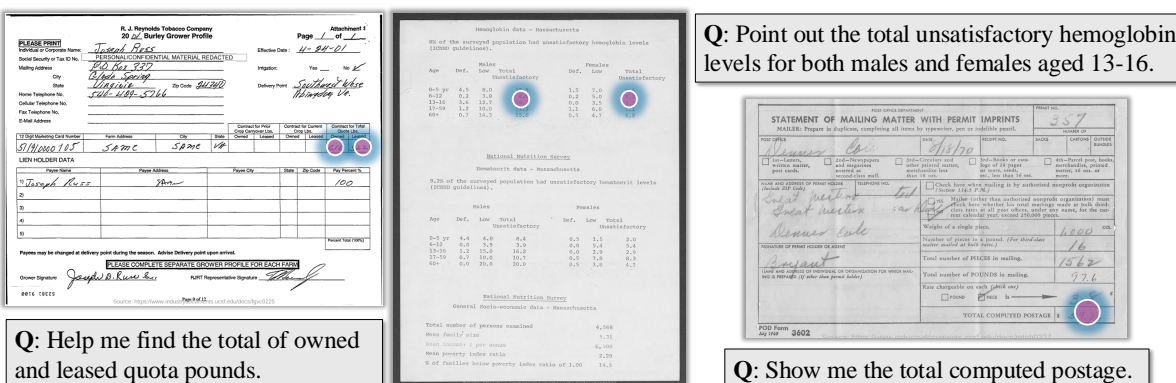


Q: How many servings do I need to fulfill the daily value of Cholesterol? **A:** 2.

Q: I have taken 1000mg of sodium today. Can I eat this without exceeding the suggested daily value? **A:** No.

Q: How many capsules per container? **A:** 56.

Figure 10: Examples from our newly collected **NutritionQA** dataset.

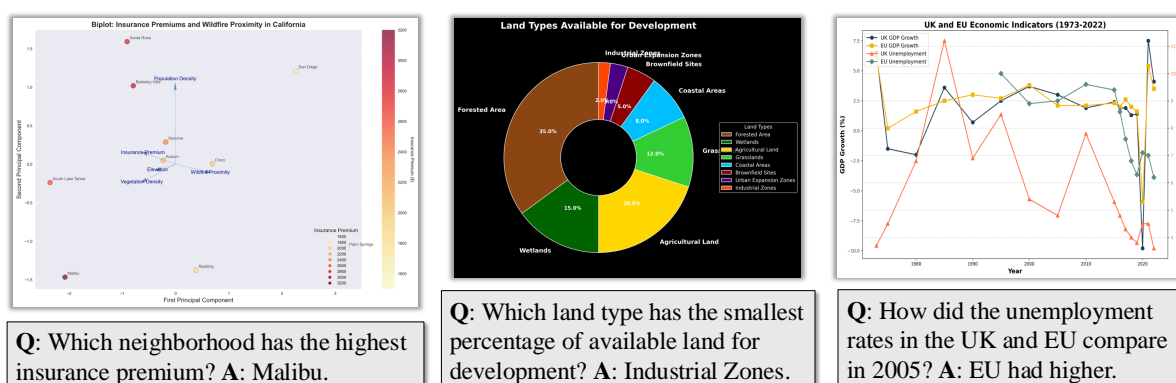


Q: Help me find the total of owned and leased quota pounds.

Q: Point out the total unsatisfactory hemoglobin levels for both males and females aged 13-16.

Q: Show me the total computed postage.

Figure 11: Examples from our newly collected **DocPointQA** dataset.



Q: Which neighborhood has the highest insurance premium? **A:** Malibu.

Q: Which land type has the smallest percentage of available land for development? **A:** Industrial Zones.

Q: How did the unemployment rates in the UK and EU compare in 2005? **A:** EU had higher.

Figure 12: Randomly selected examples from our synthetic **chart** data.

Q: What is the total monthly budget for the marketing initiatives?
A: \$2,700.

Q: What is one key indicator used in rehabilitation programs?
A: Recidivism rates

Q: What is the first step in the checklist?
A: Initial Detection.

Figure 13: Randomly selected examples from our synthetic **document** data.

Q: Which year had the lowest sales for Interior Trim?
A: 2020

Q: Which month had the highest customer foot traffic?
A: December.

Q: What is the status of of Château de Chambord?
A: Excellent.

Figure 14: Randomly selected examples from our synthetic **table** data.

Infrastructure Knot Problem

Mayor Shauna O'Connell's proposed infrastructure plan for Taunton includes a complex network of roads and bridges. The diagram below represents this network as a knot. Determine the unknotting number of this municipal infrastructure diagram, considering that each crossing change represents a major road reconstruction project.

Q: Can you answer this question?
A: 2

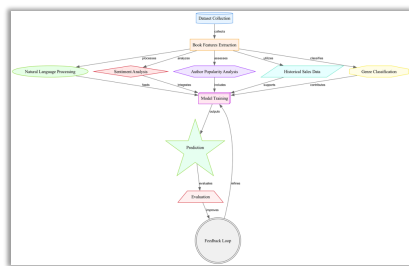
Consider a simplified model of societal change where the rate of adoption of a new idea (x) is governed by the differential equation:

$$\frac{dx}{dt} = rx(1-x) - \frac{ax^2}{1+x^2}$$

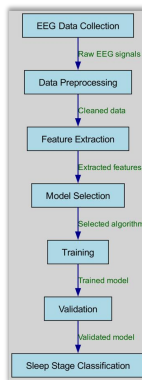
where r represents the growth rate and a represents the resistance to change. For what value of a does the system undergo a saddle-node bifurcation when $r = 1$?

Q: Give your solution to this math problem.
A: \$a = 1\$

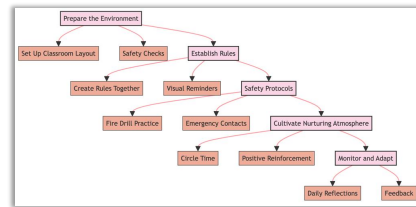
Figure 15: Randomly selected examples from our synthetic **math** data.



Q: What steps are involved immediately before making a prediction?
A: Model Training and Prediction.

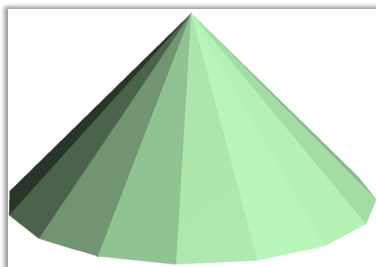


Q: What is the final outcome of the process illustrated in the diagram?
A: Sleep Stage Classification.

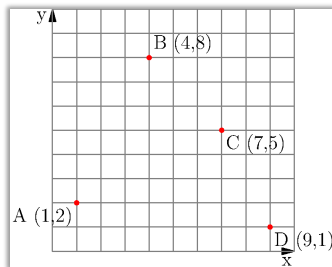


Q: Which safety practice involves emergency contacts?
A: Emergency Contacts.

Figure 16: Randomly selected examples from our synthetic **diagram** data.



Q: You estimate its height to be 100 meters and its base radius to be 150 meters. What is the volume of this volcanic cone in cm^3 ?
A: $750,000\pi \text{ cm}^3$.



Q: The turn has an angle of 33° , and the width of the track is 58 feet. What is the height difference between the inside and outside edges of the track?
A: 38 feet

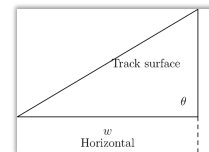
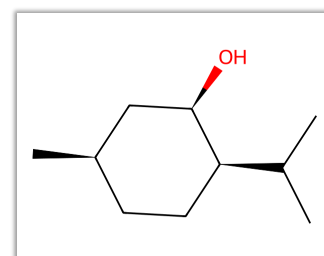
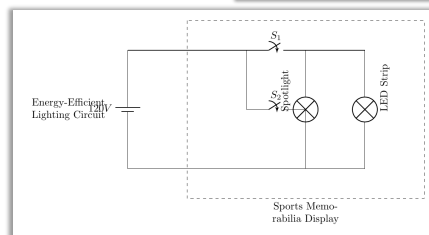


Figure 17: Randomly selected examples from our synthetic **vector graphic** data.



Q: What is the key signature of this music?
A: E major.

Q: What is the voltage of this circuit?
A: 120V.



Q: What is the main use of menthol in throat lozenges?
A: Soothing effect.

Figure 18: Randomly selected examples from our synthetic **sheet music**, **circuits** and **chemical structures**.

Online Portfolio Hosting Fee

Bill To: Digital Design Major, 123 Design Ave, Art City, AC 10101, digitaldesign@gsample.com
 Invoice Details: Invoice Number: INV-1024, Date: 2023-10-01, Due Date: 2023-10-15

Hosting Service: Provider: Squarespace, Plan: Business Plan, Monthly Fee: \$18, Annual Fee: \$216

Website Performance Analytics: Monthly Visits: 2,500, Avg. Session Duration: 2 minutes, Bounce Rate: 40%, Page Load Time: 1.5s, SEO Score: 85, Mobile Friendly: Yes

Total Due: \$18 USD

Q: Point out the page load time performance of the website, which indicates the site's speed optimization
A: (64.1, 73.7)

Conservative Issues Poll Results
 Texas State University 2023

ISSUE	SUPPORT	OPPOSITION	NEUTRAL	SAMPLE SIZE
Support for Second Amendment Rights	78%	15%	7%	500
Affirmative Action Policies	35%	57%	11%	500
Tax Cuts	62%	25%	10%	500
Border Security	85%	10%	5%	500
Abortion Rights	18%	65%	10%	500
Climate Change Policies	35%	45%	20%	500
School Choice	72%	18%	7%	500
Government Surveillance	25%	55%	10%	500
Police Funding	80%	12%	8%	500

Data collected from Texas State University students in 2023. Sample size: 500 for each issue.

Q: Generate points for all issues where opposition exceeds 60%.
A: (56.2, 61.1) (56.2, 81.4)

Q: Provide a point where users can toggle event notifications.
A: (35.7, 76.9)

Golden Age of Textiles Notifications

Manage notifications for events, exhibitions, and research in Bradford's textile history

Events & Exhibitions

Receive Event Notifications
 Stay updated about upcoming textile history events in Bradford

VIP Invitations
 Exclusive invites to private viewings and lectures

Research Updates

New Research Findings
 Notifications for the latest research in Bradford's textile industry

Published Papers
 Read the latest publications

Community & Networking

Join Textile Historians Forum
 Connect with experts and enthusiasts

Vintage Pattern Gallery
 Explore classic textile designs

9:41 5G 100%

FC Rosengård Kopparbergs/Göteborg FC

View more highlights

Eco-Friendly Printing: Sustainable Practices for the Classroom

Jane Doe, Classroom Print Services Advisor

- Reduce Paper Waste:** Adopt digital tools like Google Classroom for assignments. Encourage students to use both sides of the paper for their work.
- Use Recycled Materials:** Opt for recycled paper and use biodegradable ink for all classroom printing needs. Brands like Staples have eco-certified recycled products.
- Eco-Friendly Printing Tips:** Set printers to default double-sided printing. Use draft mode for documents that don't require high-quality prints. Implement a print quota to minimize waste.
- Nature-Inspired Aesthetics:** Utilize earthy tones such as olive green, terracotta, and beige in print materials to promote a calming and environmentally conscious classroom environment.

Q: Point out the main title of the book.
A: (50.0, 10.9)

Q: Identify which logo represents FC Rosengård in this match.
A: (22.1, 56.2)

DigitalMarketingPro Software
 Monthly Subscription Bill

Customer Details
 Name: Jane Doe, Position: Digital Marketer, Company: Creative Brands Inc., Address: 123 Marketing Lane, Johannesburg, SA, Contact: jane.doe@example.com

Billing Information
 Bill Date: October 2023, Due Date: November 5, 2023, Payment Method: Credit Card

Subscriptions

Feature	Description	Cost
Social Media Management	Scheduling and managing posts across multiple platforms	\$29.99
SEO Optimization Tools	Keyword research, on-page analysis, and performance tracking	\$19.99
Email Marketing Suite	Campaign creation, list management, and analytics	\$29.99
Analytics Dashboard	Real-time performance metrics and insights	\$19.99
Content Creation Tools	Templates for blogs, ads, and social posts	\$15.99
Total Amount		\$155.95

Please ensure payment of \$155.95 is made by November 5, 2023. Thank you for choosing DigitalMarketingPro Software for your digital marketing needs!

Q: Highlight all services that cost more than \$30.
A: (88.7, 54.6) (88.6, 61.1)

Dinner Planner

Filter Meals Add to Shopping List

Monday
 Spaghetti Bolognese (20 mins)
 Spaghetti Ground Beef Tomato Sauce

Tuesday
 Grilled Chicken Salad (15 mins)
 Chicken Breast Lettuce Caesar Dressing

Q: Show me the pasta icon for the Italian dish.
A: (15.0, 26.3)

TGS CLUB MIX

1:24 x Virgin
 1:24 x 1011 x 1011
 1:24 x 1011 x 1011
 1:24 x 1011 x 1011
 1:24 x 1011 x 1011
 1:24 x 1011 x 1011
 1:24 x 1011 x 1011
 1:24 x 1011 x 1011
 1:24 x 1011 x 1011
 1:24 x 1011 x 1011

Q: Find Michael Jackson songs that are longer than 4 minutes.
A: (9.8, 12.7) (9.8, 26.4)

Fantasy Finance Careers Portal

Filter by Category: Data Analyst, Financial Analyst, Risk Management

Senior Financial Data Analyst
 Goldman Sachs - New York, NY

Risk Management Specialist
 JP Morgan - Chicago, IL

Your Application Quest
 You're on your way to unlocking the 'Career Knight' badge!

- Applied for 3 jobs
- Complete profile
- Receive first interview

Q: Point the button to submit application for the Senior Financial Data Analyst.
A: (32.8, 25.5)

Figure 19: Randomly selected examples from our synthetic pointing data.