Plot Twist: Multimodal Models Don't Comprehend Simple Chart Details

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Abstract

Recent advances in multimodal models show remarkable performance in real-world benchmarks for chart and figure understanding like ChartQA that involve interpreting trends, comparing data points, and extracting insights from visuals. In this paper, we investigate the extent to which these models truly comprehend the underlying information in charts by posing direct, elementary questions about simple features such as axes ranges and values to examine their fundamental visual understanding abilities in the context of charts. Our questions are applied to two sets of figures: synthetic and real-world. The empirical evaluation of 5 popular multimodal models on our dataset reveals shortfalls in understanding charts and figures, contrary to what their performance on complex benchmarks might suggest. For instance, Gemini Pro Vision only achieves 57.9% accuracy on our elementary set of questions on real-world plots, while other popular multimodal models showed similar or less performance. This work highlights an important limitation of current multimodal models, and cautions against overly optimistic interpretations of their abilities based on results of canonical evaluations.

1 Introduction

Assessing chart understanding capabilities offers a crucial benchmark for evaluating foundational models' reasoning skills beyond text. Significant efforts have been made to develop benchmarks for chart understanding, such as ChartQA, that features complex, human-written questions reflecting real-world applications (Methani et al., 2019; Masry et al., 2022). Multimodal models have recently made significant progress on these evaluation benchmarks (Gemini-Team et al., 2023; Chen et al., 2023; OpenAI et al., 2023). While these models perform well on complex tasks, how do they fare with more elementary aspects of chart understanding? Can they reliably answer basic questions about the chart?

Previous work has showed that real world datasets – while very useful for ensuring the practical application – can often contain statistical patterns such that model can do well without fully understanding the relevant capability (Goyal et al., 2017; McCoy et al., 2019). Moreover, testing basic capabilities can highlight important limitations of models that do not appear in complex benchmarks (Ribeiro et al., 2020). Complex capabilities examined in these real-world benchmarks, such as obtaining insights from visualizations, are also made up of many steps: understanding the image, domain knowledge, and reasoning. This makes it harder to diagnose the cause for failures.

In this work, we probe multimodal models to understand whether they can answer elementary questions about the specific visual content in charts. This is a core capability that is essential for any model claiming proficiency in chart comprehension. We evaluate this understanding by constructing elementary probing questions. These elementary questions include straightforward questions that measure fundamental skills like identifying axis extremes and extracting plot values on synthetic plots. We first pose these elementary questions on basic, synthetic plots. Then, we select a subset of real-world ChartQA test plots and pose our simple questions to them. This allows us to directly compare model performances on complex ChartQA queries versus performance on our elementary ones (examples in Figure 1).

Our findings uncover shortcomings in these models regarding fundamental aspects of chart understanding. For example, PaLI-3 only gets 37.7% accuracy on our straightforward questions on the real-world plots. Moreover, other models such as Gemini Pro Vision and GPT-4V also get less than 60% performance. We further evaluate the robustness of these models and find that more powerful models, such as Gemini Pro Vision and GPT-4V, are often susceptible to the presence of text anno-

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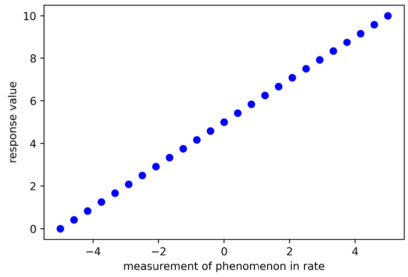
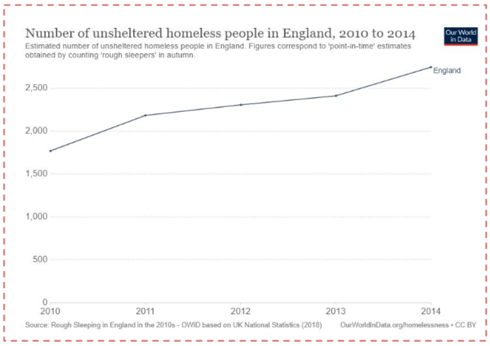


What is the minimum x value among the set of points in the figure?	4 ✗
What is the minimum value for the range on the x axis?	0 ✗

(a) Synthetic plot



(chartQA question) When does the line reach the peak?	2014 ✓
(Our question) What is the minimum value for the range on the x axis?	0 ✗

(b) Real-world plot (from ChartQA)

Figure 1: An example of our evaluation method on PaLI-3. It shows a question in our Synthetic set (top) and a question in the ChartQA dataset with its corresponding question in our real-world subset below

tations over the actual data presented in the plots, which negatively affects their accuracy. This study highlights critical limitations of current multimodal models and underscores the importance of rigorous and thorough testing especially given limited public knowledge of the data used to train them. [1]

2 Setup

In the following section, we introduce our evaluation method, designed specifically to assess the understanding of elementary features in both synthetic and real-world chart and figure understanding by multimodal models.

Evaluation Method We propose a two-pronged evaluation approach. Using synthetic data for elementary questions allows us to identify failure modes in a cost-effective manner. Subsequently, we need to determine whether these failure modes propagate to real-world scenarios and applications. To facilitate this, we create a probing dataset containing two distinct subsets of plot-question pairs. The first subset, the basic synthetic plots, and elementary questions offers a controlled environment to scrutinize specific aspects of model performance. The second subset, the real-world plots, and the same elementary questions consist of real-world figures, for which we have randomly selected a set of plots from real-world images in the ChartQA test set, supplementing them with our straightforward elementary questions. While the synthetic subset is ideal for in-depth analysis and straightforward to expand, the real-world subset allows us to test whether our findings generalize to real-world charts, even though creating this subset requires more effort and resources due to the manual process involved. Note that even though our new dataset is human-generated, it was generated to explicitly contain simple questions that only require visual understanding. This controls for the bias that creeps into very open-ended human-generated datasets. Details on these probing plots and questions are provided in the Appendix A.

Models We evaluate multimodal models that demonstrated reasonable performance on already established chart understanding benchmarks such as ChartQA. We include Gemini Pro Vision (Gemini-Team et al., 2023), GPT-4V (OpenAI et al., 2023), PaLI-3 (Chen et al., 2023), ChartLlama (Han et al., 2023) and CogVLM (Wang et al., 2024) models in our empirical analysis.

Metrics In our evaluation framework, we employ a relaxed accuracy measure for numeric answers to accommodate minor inaccuracies following previous work (Methani et al., 2020; Masry et al., 2022; Liu et al., 2022, 2023a). Specifically, we deem a numerical answer correct if it falls within 5% relative range of the "gold standard" answer and for non-numerical answer we use exact matching. However, this accuracy metric does not have a symmetric error range for small vs large values – for example, it is much more restrictive for question querying the minimum values in comparison to those querying the maximum values. Recognizing that many of our simple questions often pertain to ranges, we adopt a range-based metric to evaluate models' answers. This metric, which we term "range-based accuracy," allows for a margin of error up to 5%

[1]The dataset used in this paper is available at Chart101.

Models↓	Standard		Range-Based	
	Acc	Collective Acc	Acc	Collective Acc
Gemini Pro Vision	$52.6 \pm 0.8\%$	$25.9 \pm 1.7\%$	$73.7 \pm 0.7\%$	36.5 ± 1.8 %
GPT-4V	$50.0 \pm 0.8\%$	$23.8 \pm 1.6\%$	$68.4 \pm 0.8\%$	33.4 ± 1.8 %
PaLI-3	$31.0 \pm 0.8\%$	8.0 ± 1.0 %	$43.1 \pm 0.8\%$	21.6 ± 1.7 %
ChartLlama	$10.6 \pm 0.5\%$	$0.1 \pm 0.1\%$	$21.3 \pm 0.7\%$	6.8 ± 0.9 %
CogVLM	$30.3 \pm 0.7\%$	5.5 ± 0.9 %	$47.7 \pm 0.8\%$	19.0 ± 1.5 %

Table 1: **Elementary Questions on Synthetic Plots:** The table displays accuracy rates using standard metrics in the left columns and Range-Based Accuracy in the right columns. These results highlight the overall low performance of models with simple chart understanding questions.

Model	Plot Type		
	bar	pie	scatter
Gemini Pro Vision	53.2	88.5	37.1
GPT-4V	42.2	87.2	40.3
CogVLM	27.3	51.9	23.4
PaLI-3	26.5	65.8	38.1
ChartLlama	9.8	26.9	4.2

Table 2: **Breakdown by Plot Types:** Range-Based accuracy on the different for synthetic plots.

Models↓	ChartQA Qs	Elementary Qs
Gemini Pro V	$67.4 \pm 2.5\%$	$57.9 \pm 1.5\%$
GPT-4V	$64.0 \pm 2.6\%$	$58.0 \pm 1.5\%$
PaLI-3	$69.7 \pm 2.5\%$	$37.7 \pm 1.5\%$
ChartLlama	$30.3 \pm 2.4\%$	$25.8 \pm 1.3\%$
CogVLM	$64.0 \pm 2.6\%$	$49.8 \pm 1.5\%$

Table 3: **Questions on Real Plots:** Overall standard accuracy on ChartQA Plots comparing original vs. our simple questions. The low performance of models on our elementary questions vs. complex questions on the same plots reveals that they struggle to answer simple questions on the same visual data. This discrepancy highlights a critical gap in their ability to consistently interpret visual information.

of the entire range under consideration. We also define collective accuracy; this metric assesses the correctness of responses to a full set of questions associated with a single figure as a single number. This metric underscores the model's capacity for a comprehensive and accurate interpretation of all the basic visual features we measure for that figure.

3 Results

Models struggle to answer basic synthetic chart questions reliably. We initially assess model performance on our synthetic subset. As demonstrated in Table 1, all of our models show poor performance on both versions of our accuracy metric; with the best model Gemini Pro Vision getting 52.6% accuracy. However, even for this model, the collective accuracy of 25.9% indicates a limited comprehensive understanding of these basic chart questions on the whole chart. Public models perform considerably worse, even ChartLlama, which is specialized explicitly for charts. These findings highlight the significance of our straightforward benchmark in pinpointing the limitations of current models. We analyze model accuracy by plot type to investigate the challenges with different plots. As Table 2 shows, models find scatter plot questions more challenging than pie chart questions. This is likely because answers for pie charts are often explicit in the figures (see Figure 6), whereas scatter plots require models to interpret min/max values or ranges using less explicit cues like x-ticks. Further analysis of challenging question types for each model is in Appendix C

Accuracy gap between elementary and complex questions on the same plots. We explore whether the difficulties models face with basic chart understanding questions in synthetic settings are also evident in real-world scenarios. We ask our elementary questions on a subset of the ChartQA test sets. The ChartQA images are chosen independently of the questions paired with them in the original dataset. In the right two columns of Table 3, we compare model performance on these simple questions to their performance on the original ChartQA questions, which involve more complex reasoning. As shown, there is often a high drop in performance, such as around 10% for Gemini Pro Vision. The low performance on elementary ques-

Type of Title	Gemini Pro Vision	GPT-4V
Correct Title	77.7 %	79.4 %
No Title	37.1 %	40.3 %
Misleading	32.4 %	32.5 %

Table 4: **Changing Titles in Plots:** Range-Based accuracy across different titles. The results highlight the impact of textual information on model performance.

tions particularly highlights concerns regarding the ability of models to answer simple questions on non-synthetic plots. This is problematic because it suggests that these models may struggle to handle basic tasks even in real-world scenarios, where accuracy and reliability are crucial.

4 Robustness Tests

One key aspect of chart understanding is the models' resilience to visual changes that do not affect the informational content but only the visual presentation, such as the choice of the plotting library or variations in phrasing. Our synthetic subset allows us to comprehensively evaluate model robustness against these changes. We make targeted visual modifications to charts to assess the models' ability to maintain accurate interpretation despite superficial alterations. This evaluation is crucial for determining the real-world utility and robustness of multimodal models in chart comprehension.

Model dependence on textual cues in plots. We compare three scenarios: 1) plots without any title (baseline), 2) plots with a title containing the correct answer, and 3) plots with a title providing misleading, incorrect answers. In all cases, models are instructed to base their answers on the figure itself. The results are presented in Table 4. Our findings reveal that including the correct answer in the plot title largely enhances model performance on our dataset, with an improvement of over 15% observed for both Gemini Pro Vision and GPT-4V models. When comparing the *misleading title* scenario to the *no title* scenario, we observe that Gemini Pro Vision, in particular, is swayed by the presence of misleading textual information, suggesting a bias towards text in the figure over an accurate understanding of the plot itself.

Model dependence on visual modifications. We make minor visual modifications to the synthetic figures while ensuring they convey the same information and then pose our questions. Modifications include altering scatter plot markers, introducing grids, or switching the data visualization library from Matplotlib to JavaScript. Results are displayed in Table 5. The top row shows the range-based accuracy for PaLI-3 on the scatter plot subset at 29.5%. The table reveals that even slight visual changes highly impact the model's performance in answering the same question. For instance, adding grids to the figures reduces accuracy to 21.3%, while changing the plot style from Matplotlib's default to JavaScript-amchart improves accuracy to 43.7%. These findings highlight model's lack of robustness, as its performance is greatly affected by such small visualization changes.

Category		Range Based Acc.
Original		29.5 %
Marker	x	25.5 %
	D	28.8 %
	O	31.5 %
	+	26.9 %
Grid		21.3 %
Plot	JS-plotly	36.9 %
	JS-highchart	39.7 %
	JS-amchart	43.7 %

Table 5: **Visual Changes in Plots:** PaLI-3 Performance on figures with same informational content but small visual changes. The variability in performance highlights a lack of robustness in chart understanding.

5 Related Work

Benchmarks for multimodal reasoning. With recent advancements in foundation multimodal models, extensive efforts have been made to create valuable evaluation benchmarks for assessing multimodal models in various domains such as math reasoning (Lu et al., 2024; Cherian et al., 2022), geometric reasoning (Kazemi et al., 2023; Lu et al., 2021), geometric reasoning for coding (Rismanchian et al., 2024), visual question answering on natural images (Liu et al., 2023b; Agrawal et al., 2016; Gurari et al., 2018), medical question answering (Zhang et al., 2023), hallucination detection (Guan et al., 2024; Li et al., 2023b) and comprehensive multimodal capabilities on real-world images (Yu et al., 2023; Aho and Ullman, 1972; Fu et al., 2024; Liu et al., 2023c; Li et al., 2023a; Xu et al., 2023). In this work, we delve into the chart understanding capabilities of foundational multimodal models, exploring a critical and valuable skill set.

Chart/Figure reasoning benchmarks. Specifically, there have been valuable efforts in developing benchmarks for chart understanding, ranging from synthetic benchmarks (Kafle et al., 2018; Singh and Shekhar, 2020) featuring yes/no questions (Kahou et al., 2018), to those focusing on understanding real-world charts (Masry et al., 2022; Methani et al., 2020; Xia et al., 2024). In this work, we show a method that bridges the gap between the synthetic creation of benchmarks for figure understanding and real-world applications within the benchmark. Our evaluation method demonstrates that assessing models on basic, fundamental questions about chart understanding can uncover crucial insights into model vulnerabilities. These vulnerabilities might be overlooked if evaluations are conducted solely on synthetic or real-world images.

Multimodal foundation models. Recently, there has been a significant emergence of generalist foundational multimodal models capable of answering questions about images and reasoning upon them. Closed-source models such as Gemini Pro Vision (Gemini-Team et al., 2023), GPT-4V (OpenAI et al., 2023) (OpenAI et al., 2023), PaLI-3 (Chen et al., 2023) stand alongside open-source counterparts like LLaVA-1.5 (Liu et al., 2023b), Mini-GPT4 (Zhu et al., 2023), InstructBLIP (Dai et al., 2023) and CogVLM (Wang et al., 2024). Additionally, there are models with a specific focus on chart understanding, such as MatCha (Liu et al., 2022), ChartLlAMA(Han et al., 2023) and ChartVLM (Xia et al., 2024). In this work, we evaluate all the aforementioned models that are accessible to us and have demonstrated even a slight capability for chart understanding.

6 Conclusion

In this paper, we present a diagnostic method for evaluating multimodal foundation models, with a focus on chart understanding capabilities. Our approach combines the precision of controlled synthetic evaluations with the real-world relevance of natural data scenarios. This dual strategy is essential in the current landscape, where models often lack transparency regarding training data and operate behind APIs. Our evaluation method complements real-world datasets like ChartQA, emphasizing the need to look beyond unified metrics and thoroughly assess models to identify their failure modes. By exposing subtle limitations, our method lays the groundwork for more effective benchmarks that accurately capture previously hidden model weaknesses. We believe this work will inspire further innovation in the field, promoting a holistic and nuanced approach to model evaluation.

7 Limitations

This study emphasizes the value of using direct, unit testing with real-world application evaluations for multimodal models in the context of chart understanding. While our approach effectively identifies clear limitations and challenges within these models, there are limitations to our study:
Lack of Proposed Solutions: While we identify various model limitations, our study does not offer specific solutions to these issues. Our insights are pivotal for pinpointing effective remedies.
Causes of the Shortcomings: One limitation of this study is the ambiguity regarding the precise causes behind the observed model shortcomings. Although we hypothesize that a distributional shift between the training data and our evaluation set might play a role, further investigation is needed to confirm this and understand this. We encourage continued research and improvement in the field, enhancing the robustness and applicability of multimodal models across various real-world tasks.

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A Data Creation

Synthetic Plot-question This subset comprises a series of scatter plots, bar plots and pie charts each created using the Matplotlib or javascript libraries. These plot types are identical to those found in the ChartQA dataset, ensuring consistency and relevance in our analysis. These include scatter plots, bar charts, and pie charts. We have then carefully formulated a set of fundamental questions for each plot type aimed at basic visual understanding. We create all primary subsets of the synthetic data using the Matplotlib library. We begin by automatically generating 50 plots for each subset, followed by a manual review of each plot to ensure they meet our quality standards and are free from ambiguity. The number of questions for each subset is in Table 7.

Scatter Plots We depict straightforward mathematical functions, such as $x = y$ $x = 2x$, etc., each represented using 25 default blue marker points in scatter plots for the main subset. Each plot is accompanied by eight corresponding direct simple questions focusing on the minimum and maximum values and ranges for the x and y axes. These questions are detailed in Table 6.

Bar Charts We automatically create bar charts with the default blue Matplotlib library. We randomly sample the number of bars for each chart, ranging from 1 to 5, and assign the values of each bar randomly within the range of [-200, 200]. Each plot is accompanied by five corresponding direct simple questions focusing on the minimum and maximum values of the bars and ranges for the y axes. These questions are detailed in Table 6.

Pie Charts We automatically generate pie charts with the number of categories randomly sampled between 1 and 10. We ensure that each pie chart represents a total sum value of 100%, which is the most common use case for pie charts. The actual values are explicitly written within the categories. These questions are detailed in Table 6.

Real World Plots In this subset, we randomly sampled plots from the ChartQA test set and adapted our questions to these plots. The questions were minimally edited to ensure each question's relevance to the specific chart type and context. The ground truth answers were then included. During the annotation process, we randomly selected plots from the ChartQA test sets and ensured that our added questions meet two criteria: 1. They involve minimal modifications from our set of questions in the synthetic set, and 2. They are devoid of ambiguity. This subset is created manually, resulting in 218 questions on 70 different plots from the ChartQA human-annotated test set. For comparison, examples of comparison between our additional Questions and ChartQA test questions are presented in Figure 4.

Robustness Tests Subsets Our primary dataset, as previously outlined, consists of two distinct subsets. These subsets bridge synthetic chart understanding questions with real-world scenarios, aiming to evaluate models' fundamental abilities to comprehend charts. Another fundamental aspect of image comprehension, especially with charts, is the resilience of models to invariant visual changes in the plots. These alterations do not modify the charts' informational content but solely affect their visual presentation, such as the libraries used for plot creation or color variations. Our synthetic subset specifically facilitates a comprehensive evaluation of model robustness against these changes. By introducing targeted modifications to visual aspects of charts, we can assess model performance in maintaining accurate interpretation despite superficial alterations. This evaluation is crucial for determining the real-world utility and robustness of multimodal models in chart comprehension. To that end, we create multiple additions to the subset, changing one specific visual parts of the charts to study the models robustness to such changes. These edits include changing the choice of plot library, changing the markers of the plots, adding or removing grids, adding misleading text in the charts etc.

B Experimental Details

All the experiments in this paper are performed in April 2024.

B.1 Sampling Method

Our sampling method for assessing model performance involves querying each model five times with the same set of questions and averaging the obtained metrics to mitigate the effects of nondeterminism inherent in model responses. For the models PaLI-3, Gemini Pro Vision, and GPT-4V, we utilize the default temperature setting to closely mirror their typical usage in real-world applications. Conversely, for the models CogVLM and ChartLlama, we adjust the temperature to 0.7, based on preliminary tests indicating optimized performance at this setting. This method ensures that our evaluation reflects both the robustness and the real-world applicability of these multimodal models.

B.2 Model Sizes

We include Gemini Pro Vision (Gemini-Team et al., 2023), GPT-4V (OpenAI et al., 2023), PaLI-3 (Chen et al., 2023), ChartLlama (Han et al., 2023) and CogVLM (Wang et al., 2024) models in our empirical analysis. We use Gemini 1.0 Pro Vision, and GPT-4V through their APIs. All experiments for these two models are performed in the first week of April 2024 (mentioning the data as the models behind APIs can change over time). We use ChartLlama-13B and CogVLM-17B. The PaLI-3 model is of size 5B.

B.3 Prompts

For all our question-answering tasks, we use the prompt "Answer the question based on the Figure + [Question]." for PaLI-3, CogVLM and ChartlLamma. For the robustness test of exploring models' dependence on textual cues in the plot, we further emphasize the figure by changing the prompt to "Answer the question only based on the figure + [Question]." For automated extraction of the answers, we instruct Gemini Pro Vision and GPT with another prompt as presented in Figure 2.

> Please answer the following question based on the plot/figure with the response in the same format: `"The answer is ANS. I hope the answer is correct."` In which the ANS represents the correct answer. Be concise and accurate in your reply.

Figure 2: Prompt for Gemini and GPT Models

B.4 Automated Evaluation

To facilitate automated evaluation, we instruct all models to format their respon'ses in a specific structure: "The answer is ANSWER." While Gemini Pro Vision and GPT-4V consistently adhere to this format, the other models frequently deviate from it. To address this inconsistency, we employ the GPT-3 turbo model to reformat the responses into the required structure before extracting the answers. This additional step ensures uniformity in response formatting across all tested models, enabling more accurate automated analysis. Prompt is in Figure 3

Synthetic subset	Questions
scatter plots	What is the maximum/minimum value among the set of points plotted in the figure? What is the approximate maximum/minimum value for the range on the x/y-axis?
bar chart	What is the maximum/minimum value among the set of bars plotted in the figure? How many bars are in the figure? What is the maximum/minimum value for the range on the y-axis?
pie chart	What is the maximum/minimum value among the set of categories in the figure? How many categories are presented?

Table 6: Question templates for synthetic dataset

Synthetic subset	Number of Questions
scatter plots	336
bar chart	250
pie chart	141

Table 7: Question templates for synthetic dataset

C More Analysis

What type of questions are the hardest? Following the approach of segmenting model performance by plot types, our use of synthetic data facilitates a similar analysis based on question types. This approach enables us to evaluate and pinpoint the particular performance characteristics of each model, allowing for a detailed investigation into the distinct behavioral patterns and challenges models exhibit when responding to different kinds of questions. The outcomes of this question-type-specific performance evaluation are presented in Figures 9 and 8, which detail the distinct range-based accuracy and response patterns of each model across the range of question types examined. For example, we first observe distinct behaviors among the models: while GPT-4V demonstrates its strongest performance on questions concerning the minimum range on the x-axis, Gemini Pro Vision and PaLI-3 struggle the most with this type of question when dealing with scatter plots. As discussed earlier, these detailed insights into models' specific limitations are vital for understanding the reliability of model responses and guiding the development of effective solutions.

Extract the concise answer from the model's response as shown in the examples below, making sure the answer is in this format: "The answer is ANS. I hope the answer is correct."

Example 1:

Question: "How many food items are shown in the bar graph?"
Model Answer: "<extra_id_0> 0"
Extracted Answer: The answer is 0. I hope the answer is correct.

Example 2:

Question: "How many bars are in the figure?"
Model Answer: "<extra_id_0> There are three bars in the figure."
Extracted Answer: The answer is three. I hope the answer is correct.

Example 3:

Question: "Find missing data of the sequence 24, _, 32, 33, 42?"
Model Answer: "<extra_id_0> 33"
Extracted Answer: The answer is 33. I hope the answer is correct.

Example 4:

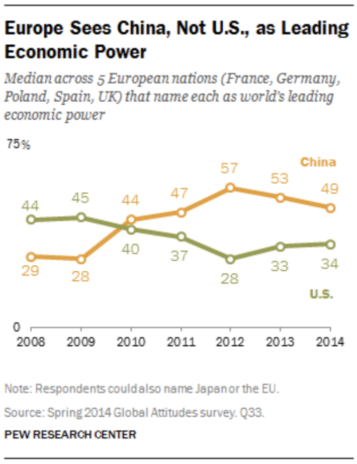
Question: "Which country has the highest secondary graduation rate in 2018?"
Model Answer: "<extra_id_0> Italy"
Extracted Answer: The answer is Italy. I hope the answer is correct.

Your Task:

Given the question and model answer below, extract the concise answer.

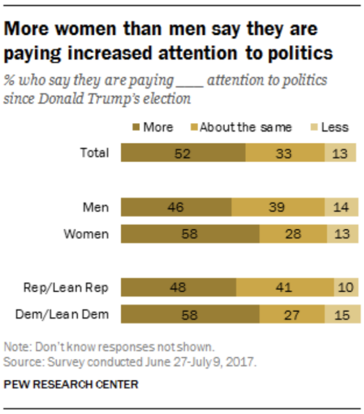
Question: "{question}"
Model Answer: "{model_raw_output}"
Extracted Answer:

Figure 3: Prompt for Extraction of Answers for Automated Evaluation



ChartQA: What is the greatest gap value between the orange and the green lines?

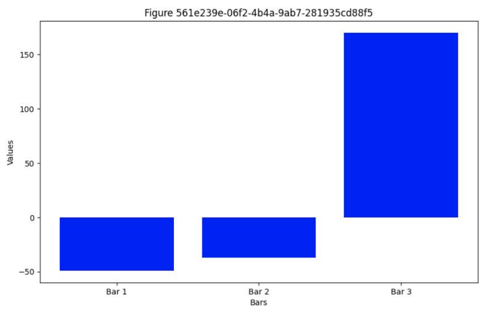
Our added Q: What is the maximum approximate value for the range on the x-axis?



ChartQA: What's the total value of the More bar?

Our added Q: How many bars are plotted in the figure?

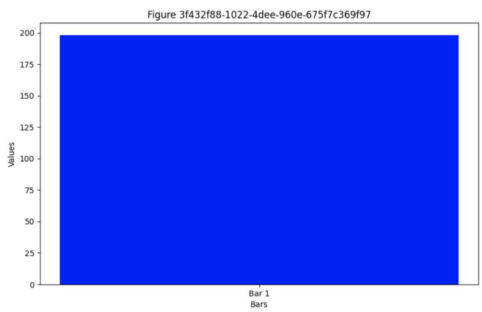
Figure 4: More examples of questions from our simplified dataset alongside those from the ChartQA dataset, with corresponding questions from our set. ChartQA human-written questions vary in complexity, from the more straightforward at the bottom of the example to those requiring complex reasoning at the top. In contrast, our questions are consistently structured to be simple.



Q1: What is the maximum value among the set of bars plotted in the figure?
Accepted Range of Answers for Accuracy: [161.5, 178.5]
Accepted Range of Answers for Range-Based Accuracy: [158, 182]

Q2: What is the minimum value among the set of bars plotted in the figure?
Accepted Range of Answers for Accuracy: [-51.45, -46.55]
Accepted Range of Answers for Range-Based Accuracy: [-61, -37]

Q3: How many bars are in the figure?
Accepted Answer for Accuracy: 3
Accepted Answer for Range-Based Accuracy: 3

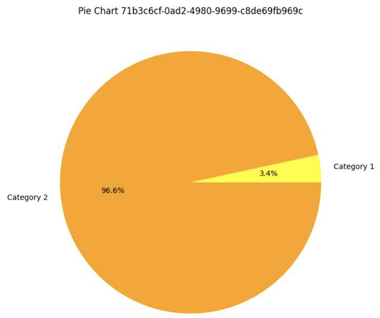


Q1: What is the maximum value among the set of bars plotted in the figure?
Accepted Range of Answers for Accuracy: [188.1,207.9]
Accepted Range of Answers for Range-Based Accuracy: [178.6,208.4]

Q2: What is the minimum value among the set of bars plotted in the figure?
Accepted Range of Answers for Accuracy: [188.1,207.9]
Accepted Range of Answers for Range-Based Accuracy: [178.6,208.4]

Q3: How many bars are in the figure?
Accepted Answer for Accuracy: 1
Accepted Answer for Range-Based Accuracy: 1

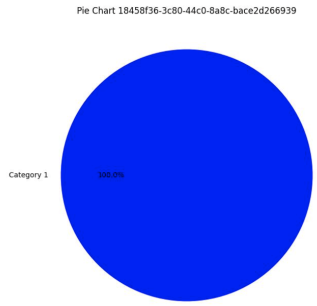
Figure 5: Examples of questions from our synthetic dataset for the barcharts



Q1: What is the maximum value among the set of categories in the figure?
Accepted Range of Answers for Accuracy: [91.7, 101.4]
Accepted Range of Answers for Range-Based Accuracy: [91.6, 101.6]

Q2: What is the minimum value among the set of categories in the figure?
Accepted Range of Answers for Accuracy: [3.23, 3.57]
Accepted Range of Answers for Range-Based Accuracy: [0, 8.4]

Q3: How many categories are presented?
Accepted Answer for Accuracy: 2
Accepted Answer for Range-Based Accuracy: 2

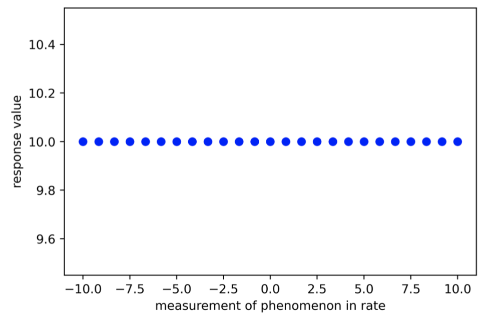


Q1: What is the maximum value among the set of categories in the figure?
Accepted Range of Answers for Accuracy: [95, 100]
Accepted Range of Answers for Range-Based Accuracy: [95, 100]

Q2: What is the minimum value among the set of categories in the figure?
Accepted Range of Answers for Accuracy: [95, 100]
Accepted Range of Answers for Range-Based Accuracy: [95, 100]

Q3: How many categories are presented?
Accepted Answer for Accuracy: 1
Accepted Answer for Range-Based Accuracy: 1

Figure 6: Examples of questions from our synthetic dataset for the piecharts



Q1: What is the minimum x value among the set of points plotted in the figure?
Accepted Range of Answers for Accuracy: [-10.5, -9.5]
Accepted Range of Answers for Range-Based Accuracy: [-11.1, -8.9]

Q2: What is the maximum x value among the set of points plotted in the figure?
Accepted Range of Answers for Accuracy: [9.5, 10.5]
Accepted Range of Answers for Range-Based Accuracy: [8.9, 11.1]

Q3: What is the minimum y value among the set of points plotted in the figure?
Accepted Range of Answers for Accuracy: [9.5, 10.5]
Accepted Range of Answers for Range-Based Accuracy: [9.95, 10.05]

Q4: What is the maximum y value among the set of points plotted in the figure?
Accepted Range of Answers for Accuracy: [9.5, 10.5]
Accepted Range of Answers for Range-Based Accuracy: [9.95, 10.05]

Q5: What is the approximate minimum value for the range on the y-axis?
Accepted Range of Answers for Accuracy: [9.01, 9.96]
Accepted Range of Answers for Range-Based Accuracy: [9.43, 9.54]

Q6: What is the approximate maximum value for the range on the y-axis?
Accepted Range of Answers for Accuracy: [10.02, 11.07]
Accepted Range of Answers for Range-Based Accuracy: [10.49, 10.65]

Q7: What is the approximate minimum value for the range on the x-axis?
Accepted Range of Answers for Accuracy: [-11.55, -10.45]
Accepted Range of Answers for Range-Based Accuracy: [-12.1,-9.9]

Q8: What is the approximate maximum value for the range on the x-axis?
Accepted Range of Answers for Accuracy: [10.45, 11.55]
Accepted Range of Answers for Range-Based Accuracy: [9.9, 12.1]

Figure 7: Examples of questions from our synthetic dataset for the scatterplot

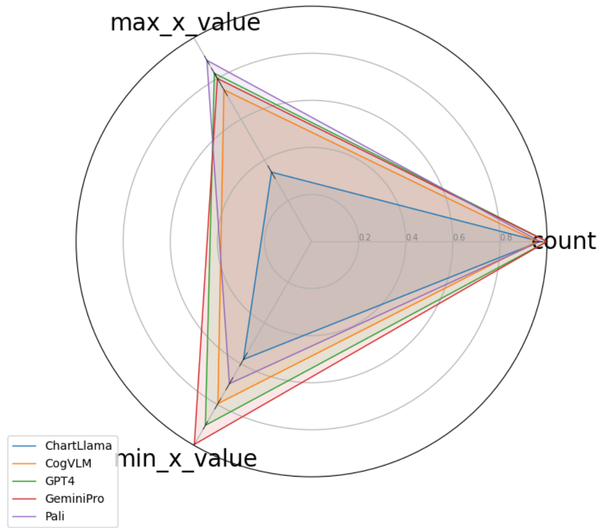
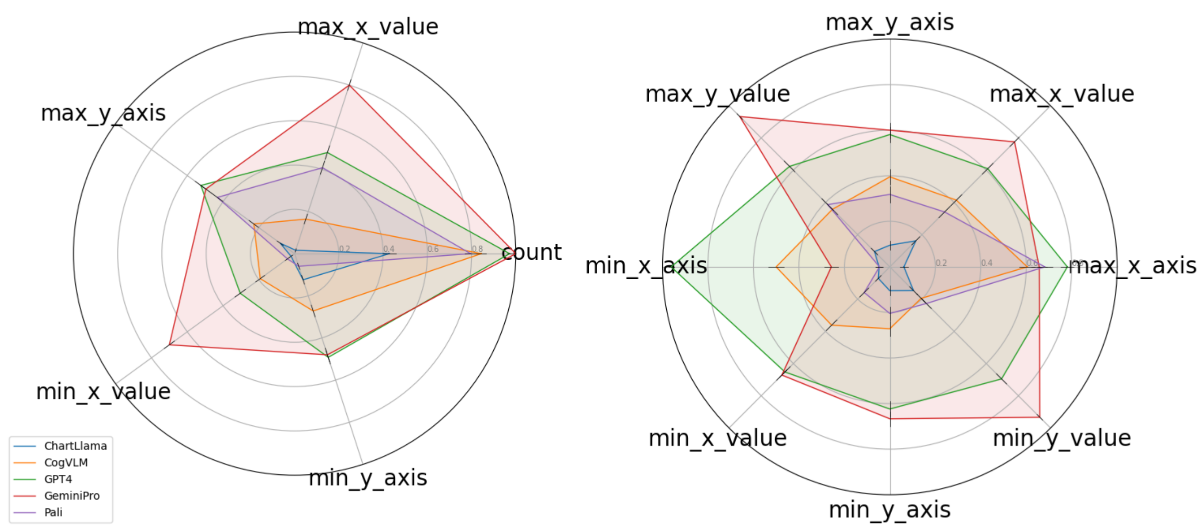


Figure 8: Radar chart depicting the range-based accuracy of different models in response to various question types in our pie charts.



(a) Synthetic Bar Chart Questions

(b) Synthetic Scatter Plot Questions

Figure 9: Radar chart depicting the range-based accuracy of different models in response to various question types, highlighting the distinct limitations each model exhibits with respect to specific types of questions. ,