

OpenCQA: Open-ended Question Answering with Charts

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Abstract

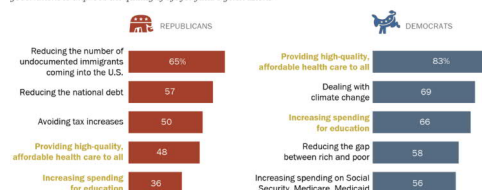
Charts are very popular to analyze data and convey important insights. People often analyze visualizations to answer open-ended questions that require explanatory answers. Answering such questions are often difficult and time-consuming as it requires a lot of cognitive and perceptual efforts. To address this challenge, we introduce a new task called OpenCQA, where the goal is to answer an open-ended question about a chart with descriptive texts. We present the annotation process and an in-depth analysis of our dataset. We implement and evaluate a set of baselines under three practical settings. In the first setting, a chart and the accompanying article is provided as input to the model. The second setting provides only the relevant paragraph(s) to the chart instead of the entire article, whereas the third setting requires the model to generate an answer solely based on the chart. Our analysis of the results show that the top performing models generally produce fluent and coherent text while they struggle to perform complex logical and arithmetic reasoning.

1 Introduction

Using data visualizations such as bar charts and line charts to discover critical insights, and explain them to others is at the heart of many decision making tasks (Munzner, 2014). Often, people explore such visualizations to answer high-level questions that involve reasoning and explanations. For example, Figure 1 shows an open-ended question which cannot be answered by a single word or phrase, rather it requires an explanatory answer. Answering such questions can be time consuming and mentally taxing as they require significant amounts of perceptual and cognitive efforts. For the particular question in Figure 1, the user needs to find relevant marks (bars) in the given charts, compare their values and perform reasoning over them to generate an explanatory answer. Thus, the research question

Republicans and Democrats have different ideas about what government should do to improve the lives of future generations of Americans

% of Republicans/Democrats saying each of the following should be a top priority in order for the federal government to improve the quality of life for future generations



Question: Compare the Democrats and Republicans views about providing health care to the population?

Answer: While 83% of Democrats say providing high-quality, affordable health care for all should be a top priority, a much smaller share of Republicans (48%) agree.

Figure 1: A question-answer pair from our dataset.

we address in this paper is: can we build systems to automatically answer such open-ended questions about charts with descriptive texts?

Chart Question Answering (CQA) is a task where the goal is to take a chart and a natural language question as input and generate the desired answer as output (Hoque et al., 2022). While CQA has received growing attentions in the last few years, existing datasets only focus on close-ended (factoid) questions where the answer is a word or phrase (Kahou et al., 2017; Kafle et al., 2018; Chaudhry et al., 2020; Singh and Shekhar, 2020). These datasets typically use predefined templates to generate synthetic questions and answers to these questions come from a closed vocabulary (e.g., ‘yes’, ‘no’, ‘x-axis-label’). PlotQA (Methani et al., 2020) introduces some open-vocabulary questions that require aggregation operations on the underlying chart data; the answer is still however a number or a word/phrase obtained from the chart. Kim et al. (2020) attempt to automatically explain how the model computes the answer but only for close-ended ones. To our knowledge, there are no datasets on CQA with open-ended questions.

In this work, we introduce a novel task named, OpenCQA in which the system takes a chart and a question as input and is expected to produce a de-

scriptive answer as output like the one in Figure 1. This task is multidisciplinary and challenging in nature as it involves natural language generation (NLG), information visualization and computer vision. It differs from the data-to-text and reading comprehension, because unlike text or tables, charts serve a different communicative goal by creating visual representation of data. Readers can quickly notice important patterns, trends, and outliers from such visual representation which cannot be easily observed from a table of raw data (Munzner, 2014). By looking at a line chart, one can quickly discern an important trend whereas scatterplots may visually depict correlations and outliers. Existing NLG approaches for tables do not consider such chart features in the generation.

We have developed a benchmark dataset for OpenCQA consisting of 7,724 human-written open-ended questions about a variety of real-world charts and the associated descriptive answers. We formulate three practical task settings. In the first setting, a chart and the article containing the chart is provided as input, and the model generates an answer to an open-ended question. This setting poses extra challenge as articles often contain paragraphs that are irrelevant to the questions. To make the task more focused, the second setting provides only the relevant paragraph(s) to the chart. Hence we can measure the models' ability to answer a question without the effect of extra noise from irrelevant text. The third setting is more challenging as the related text is not provided and the model needs to generate an answer solely based on the chart. This is more relevant to real world scenarios where charts are not associated with any explanatory text.

Since the proposed task is completely new, we adapt a variety of state-of-the-art models that utilize multimodal, data2text and extractive summarization methods to serve as strong baselines. We conducted automatic and qualitative evaluations and observe that the top performing models are quite fluent and coherent in generating summaries but lack in complex logical reasoning and inference. Our codebase is publicly available at <https://github.com/vis-nlp/OpenCQA>.

2 Related Work

Our work is related to three lines of prior work.

(i) Chart Summarization Mittal et al. (1998) and Ferres et al. (2013) adopt a planning-based architecture and used templates to describe charts

with texts. These methods can only describe how to read a chart without summarizing any insights from the chart. Demir et al. (2012) compute statistics to generate bar chart summaries and simultaneously construct sentence- and discourse-level structures. Chen et al. (2019) use a ResNet (He et al., 2016) to encode a chart and a LSTM decoder to generate a caption. All these studies generate summaries using predefined templates, which may lack naturalness and variations in terms of grammatical structure and lexical choices. Obeid and Hoque (2020) and Kantharaj et al. (2022a) use transformer-based models while Spreafico and Carenini (2020) use an LSTM based encoder-decoder model to generate chart summaries in a data-driven fashion. But their models only focus on generating a summary to describe the chart rather than focusing on a specific relevant portion of a chart to answer a question which is the main focus of our work.

(ii) Visual Question Answering (VQA) VQA involves answering a question regarding an input image (Antol et al., 2015). To relate the question and the image effectively, researchers focus on fusing textual and visual information together (Lu et al., 2019; Talmor et al., 2021). Cho et al. (2021) introduce VL-T5 and VL-BART as pre-trained vision-language models which achieved competitive results on VQA tasks. Unlike images with real-world objects and scenes, charts encode data using marks (bars, lines) and have inherent structure which makes the chart QA task quite different from VQA (Masry et al., 2022).

(iii) Data2text Generation Data2text models generate a descriptive summary from a data table. Previous work has focused on specific domains such as sports (Barzilay and Lapata, 2005; Wiseman et al., 2017), weather-forecast (Reiter et al., 2005), recipe (Yang et al., 2017) and biography (Lebret et al., 2016). Others (Parikh et al., 2020; Chen et al., 2020a) have focused on open-domain tasks. Many of these methods use an LSTM-based encoder-decoder architecture (Mei et al., 2016; Lebret et al., 2016; Wiseman et al., 2017), while Gong et al. (2019) find that transformers yield more fluent and coherent outputs. Few approaches focus on generating textual facts with logical inference rather than stating simple facts that can be easily retrieved from the data table (Chen et al., 2020a,b). Unlike the task with data tables, our task involves understanding visual features of the charts and the

natural language questions to perform reasoning in order to generate (or extract) texts as answers.

3 Dataset Construction

3.1 Data Collection & Annotation

Building a dataset with open-ended questions and human-written descriptive answer is challenging because there are not many publicly available real-world sources with charts and related textual descriptions. After exhaustive search, we decided to use charts from Pew Research (pewresearch.org). Pew serves as a suitable source because the articles are written by professional writers covering opinions, market surveys, demographic trends and social issues. The articles are often accompanied by a variety of real-world charts and their summaries.

We collected 9,285 chart-summary-article triples scraped from nearly 4,000 articles. However, not all of the charts are suitable for creating open-ended questions. For example, some charts maybe too unconventional or too complex while a few others have poor resolution. Similarly, the text accompanying the chart may not discuss data values in the chart and instead refer to other external background facts. Hence, we manually went over all the charts to retain 7,724 samples that we deemed suitable for our study. In particular, we filtered out 1,019 samples as too complex and 542 as samples we cannot make an open-ended question.

We perform an annotation study on the collected chart data to create question-answer pairs following the four steps below (see Table 8 for an illustrative example). More details of the data collection and annotation process are provided in Appendix A.1.

(1) Question-answer Creation We asked each crowdworker from Amazon Mechanical Turk to answer three existing questions (created by another crowdworker) for three separate charts respectively, and create three new question-answer pairs for three new charts. They were provided with the chart and the summary, and were asked to select portions of the text as an answer to the question. The selected segments can be noncontiguous. In this way, we collected two answers from different workers for each question, to verify answers and to remove any potential bias in answer selection.

(2) Question Validation and Editing After collecting the question-answer (QA) pairs, this and the next two steps are performed by five internal annotators who are native speakers of English and

have research background in summarization. Each QA pair is first examined by an annotator who first checks if the question is open-ended in nature, and edits the questions when the question is vague or incomplete, or not answerable from the charts. Then, the remaining annotators analyze the questions in terms of grammatical correctness and edit them as needed. Overall, the question was edited in 53% question-answer pairs. In this 22.7% cases were minor changes (less than 30% tokens changed), 15.5% cases were moderate changes (between 30% and 60% tokens changed) and 14.8% were major changes (over 60% tokens changed).

(3) Disagreement Resolution As mentioned, we obtain two answers from the crowdworkers for each chart-question pair. To resolve any potential bias from one and/or disagreement between the two answers, we build an annotation interface where an annotator can either choose one of the two answers, or select a new answer from the given summary. The annotator checks whether the answer contains irrelevant information to the question or any text that are not derivable from the chart (*e.g.*, background information). For 18.4% cases, the two answers matched exactly. For 68.2% samples, the two answers still had high overlaps (over 90% token matches); for another 10.1% the overlaps between the answers were moderate (between 30% and 90% token matches) and for the remaining 3.3%, the token matches between answers were less than 30%. While resolving the disagreements between crowdworkers, in 96% cases the annotators chose one of the two answers while for other 4% they selected a new answer from the summary.

(4) Decontextualization In some cases, crowdworkers may have left out important information from the summary that is relevant to the question while in other cases, they may have included information that is not derivable from the chart. Thus, after selecting the most appropriate answer, annotators edit it further by adding tokens from the summary or removing tokens as necessary, which is taken as the *extractive answer* for the dataset. Also, if needed, they replace the occurrence of a pronoun with its antecedent (a proper noun) in cases where the entity is unknown, to put the answer in context, which is the *abstractive answer*. After this, annotators did another final pass through all the annotations to ensure textual quality of answers and inclusion or exclusion of relevant or irrelevant tokens respectively.

Type	Example	%
Identify	What are the current thoughts on direct democracy?	37%
Summarize	Explain the distribution of people who know a transgender person?	37%
Compare	Compare Americans and Germans views about the world economic leader?	20%
Discover	How do Americans' see the coronavirus statistics?	6%

Table 1: Example and distribution of question types among 100 randomly selected questions. The corresponding charts of these examples are shown in Figure 6.

3.2 Dataset Analysis

Figure 2a represents some basic statistics about the dataset. The questions and titles are generally short with both under 21 tokens on average. The percentage of tokens overlapping between the extractive answer and the article is 7% on average. Other characteristics of our dataset are as follows.

- **Chart Types and Topics** Our dataset contains a variety of chart types (Figure 2a). The most common is bar charts (71.7%), for both simple as well as stacked and group bar charts. The next most common type is line charts (24.6%). Other types include area charts, scatter plots and pie charts. The dataset also covers a diverse range of topics including politics, technology, society and media (Figure 2b); about half of the charts cover *U.S. Politics & Policy* due to the nature of the dataset.

- **Question Types** We further analyze the question types using 100 randomly sampled question-answer pairs from our dataset. Table 1 shows the distribution of questions across four main types. Our categorization of questions are based on the specific analytical tasks with visualizations one would have to perform to answer the question (Munzner, 2014). The four categories are: (i) *Identify*: questions that require identifying a specific target (e.g., a data item or a data attribute) from the chart and describing the characteristics of that target; (ii) *Compare*: questions that require comparisons between specified targets from the chart; (iii) *Summarize*: questions that require summarizing the chart based on specified statistical analysis tasks (e.g., describing data distribution, outliers(s), and trend(s)); and (iv) *Discover*: questions that require analyzing the whole chart to derive key insights through inference and reasoning. Unlike the *summarize* task there is no explicit analytical task that is specified in a *discover* type question.

From Table 1, we notice that people often ask to locate one or more portions of a chart (identify and compare) and then characterize them to answer the question. They may also ask for a descriptive

answer of some trends or data distributions. In contrast, questions that require the user to focus on the whole chart (e.g., discovery) are fewer. This suggests that unlike the chart summarization problem which focuses on the whole chart, OpenCQA problem requires the model to identify relevant portions of the chart to answer the question.

4 OpenCQA Models

Problem Definition For our OpenCQA problem, we consider three task settings. In the first setup, the model takes a chart and the article containing the chart as input and extracts an answer to an open-ended question. The data for this task can be represented as a tuple of 6 elements $\mathcal{D} = \{\langle C, T, M, Q, D, A \rangle_n\}_{n=1}^N$, where C, T, M, Q, D and A represent the chart image, title, metadata, question, document (article) text and answer text, respectively. The metadata $M = \langle C_{\text{label}}, C_{\text{bbox}} \rangle$ consists of the chart labels that are text segments extracted from the chart through OCR (e.g., axis labels, data labels) and their respective bounding boxes. In the second setup, the chart summary is provided as input instead of the whole article. The dataset in this setup can be represented as $\mathcal{D} = \{\langle C, T, M, Q, S, A \rangle_n\}_{n=1}^N$, where S represents the chart summary. In the third setup, the chart summary is not accessible, and the model must rely only on the chart. This is a more difficult and interesting problem setting since real world charts often do not come with explanatory summaries. In this setting, for an input $I = \langle C, T, M, Q \rangle$, the model has to learn to generate an explanatory answer A .

For training the models, we use state-of-the-art *extractive* and *generative* QA models. The supervision of extractive models are *extractive* answers whereas for the generative models *abstractive* or edited (as described in Section 3.1) answers are used. Note that the third task setting applies to only generative models, whereas the first and second settings apply to both extractive and generative models. We describe the models below (implementation details are in Appendix A.2).

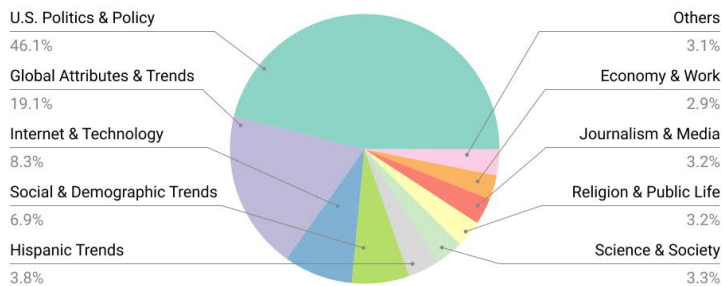
4.1 Extractive Models

We adopt two extractive models for the two problem setups where the models extract the answer to the question from the input summary or article.

- **BERTQA** (Chadha and Sood, 2019) is an extractive QA model that uses directed coattention layers (Xiong et al., 2016) to improve the performance of the original BERT model (Devlin et al.,

Statistics (on average)		
Tokens in article		1268.91
Tokens in summary		123.35
Tokens in title		17.94
Tokens in question		11.88
Tokens in abstractive answer		56.41
Tokens in extractive answer		56.21
Percentage of tokens extracted from the summary		52%
Percentage of tokens extracted from the article		7%
Type	Simple	Complex
Bar	712	4,823
Line	234	1,667
Area	7	4
Scatter	0	42
Pie	235	0
Total	1,188	6,536

(a) Dataset Statistics and Chart Types



(b) Distribution of topics.

Figure 2: (left) Dataset Statistics and Chart Types, (right) Topic Distribution

2019). In this approach, we first pass the question and the text (article or summary) through a BERT model to get the (self-attention based) representations. It then calculates the cross attention from the question to text and text to question and concatenates the resulting vectors to predict the start and end points of the answer span.

- **ELECTRA** (Clark et al., 2020) proposes a self-supervised representation learning method that emphasizes computational efficiency. In contrast to Masked Language Modeling (MLM), it uses Replaced Token Detection or RTD as the pretraining task. The training process is inspired by the training of Generative Adversarial Networks or GANs (Goodfellow et al., 2020). The training examples are first passed to a generator (typically a small MLM-based model) to replace some of the tokens in the input with other probable but incorrect tokens. ELECTRA (the discriminator) is then trained to distinguish between the “original” vs. “replaced” tokens in the input. This binary classification task is applied to every token, hence it requires fewer training examples compared to MLM training. ELECTRA achieves state-of-the-art results on SQuAD 2.0 (Rajpurkar et al., 2018). We use the same experimental setup as with the BERTQA model.

4.2 Generative Models

- **GPT-2** (Radford et al., 2019) trains a transformer decoder on the unlabelled BooksCorpus dataset (Zhu et al., 2015) using a conditional language modelling objective. Their pretrained model can be fine-tuned on downstream tasks such as textual entailment, similarity and question answering. We fine-tune GPT-2 under the three tasks where all the input elements in each task setting are concatenated as conditioning input to predict the answer.
- **BART** (Lewis et al., 2020) uses a standard encoder-decoder transformer architecture. Its pre-training task involves denoising, where text spans

in the input text are replaced with a single mask token, and the decoder is tasked to predict the original input sequence. BART has been shown to achieve state-of-the-art performance on text generation tasks such as summarization. In each of our three task settings, we concatenate the corresponding inputs and feed into the model for fine-tuning.

- **T5** (Raffel et al., 2020) is a unified encoder-decoder transformer model that converts language processing tasks into a text2text generation format. It is first pretrained with a ‘fill-in-the-blank’ denoising objective, where 15% of the input tokens are randomly dropped out. The spans of consecutive dropped-out tokens and dropped-out tokens that stand alone are then replaced by special sentinel tokens. Each sentinel token is assigned a token ID that is unique in the input sequence. The decoder then learns to predict those dropped-out tokens, delimited by the same input sentinel token plus a final sentinel token. We fine-tuned T5 on our tasks using the same input format as with BART.

- **VLT5** (Cho et al., 2021) is a T5-based framework that unifies the Vision-Language (VL) tasks as text generation conditioned on multimodal inputs. The input consists of both textual tokens and visual features of objects from the image extracted by Faster R-CNN (Ren et al., 2015). The model is pretrained on multiple multimodal tasks: language modeling, visual QA, visual grounding, image-text matching and grounded captioning. We fine-tuned VL-T5 on our OpenCQA generative task in the following manner. For the textual input, we use the same input format as T5. For the visual input, we extract the visual features of different marks in the chart image (e.g., bars, lines) using Mask R-CNN (He et al., 2017) with Resnet-101 as its backbone.

- **CODR** (Prabhumoye et al., 2021) proposes a document grounded generation task, where the model uses the information provided in a document to enhance text generation. In their setup, the context

Models	Type	ROUGE_F (1/2/L) ↑	CS ↑	BLEURT ↑	CIDEr ↑	BERTScore ↑	BLEU ↑
Setup 1: With Article Provided							
BERTQA	Extractive	22.81/8.53/16.63	28.17%	-0.692	0.983	85.00	9.58
ELECTRA	Extractive	57.67/50.09/53.89	54.73 %	0.066	5.100	91.01	38.79
BART	Generative	50.68/38.95/45.55	54.29%	-0.017	4.121	91.08	23.91
T5	Generative	66.57/60.40/ 63.46	68.24%	0.103	5.437	93.53	41.28
VLT5	Generative	58.90/49.97/54.82	66.06%	0.076	5.227	92.34	40.06
GPT2	Generative	16.71/66.57/13.75	14.71%	-0.745	0.814	82.05	0.99
CODR	Generative	14.58/1.31/11.37	3.4%	-1.155	0.051	81.90	0.43
Setup 2: With Summary Provided							
BERTQA	Extractive	70.97/67.77/69.34	85.28%	0.297	7.177	94.65	66.33
ELECTRA	Extractive	76.24/74.33/ 75.48	92.57%	0.378	7.823	96.06	65.40
BART	Generative	66.41/61.86/64.41	68.71%	0.257	6.613	93.85	38.42
T5	Generative	75.77/73.51/74.51	81.73%	0.369	7.728	95.22	57.93
VLT5	Generative	75.07/72.35/73.86	85.36%	0.376	7.597	95.20	59.80
GPT2	Generative	14.29/11.13/13.42	22.00%	-0.782	1.725	49.18	12.68
CODR	Generative	13.81/0.76/10.25	2.480%	-1.039	0.038	81.87	0.31
Setup 3: Without Summary Provided							
BART	Generative	40.29/21.40/32.48	49.07%	-0.166	2.260	89.69	7.41
T5	Generative	41.12/22.09/32.97	52.30%	-0.173	2.357	89.59	9.28
VLT5	Generative	42.87/22.60/ 33.29	54.47%	-0.134	2.447	89.53	14.73
GPT2	Generative	28.55/11.26/22.46	32.00%	-0.493	1.314	85.05	4.89
CODR	Generative	14.67/1.05/10.90	4.14%	-1.170	0.053	81.86	0.32

Table 2: Evaluation results for different models on the test set. ↑ means higher is better, ↓ means lower is better. All models use the OCR-extracted data and chart title in the input. 70:15:15 fully random split is used for train:test:val.

and source documents are concatenated and passed to a BART encoder to get a contextualized representation of the document. Then the same encoder is applied to the context alone and both representations are finally concatenated and passed to the BART decoder to generate the text. We fine-tune the pretrained BART encoder and decoder following the approach of CODR for OpenCQA by taking the question as the context and concatenating the rest of input elements as the grounded document.

5 Evaluation

5.1 Automatic Evaluation

Measures We utilized six measures for automatic evaluation. **BLEU** (Post, 2018) measures n -gram overlaps between the model generated text and the reference. It is a precision oriented measure and is calculated by taking the geometric mean of BLEU1-4 and multiplying by the exponential of brevity penalty. **ROUGE** (Lin, 2004), on the other hand, is recall based and it measures n -gram overlaps between the model generated text and the reference as a percentage of n -grams in reference summaries. We report ROUGE-F score.

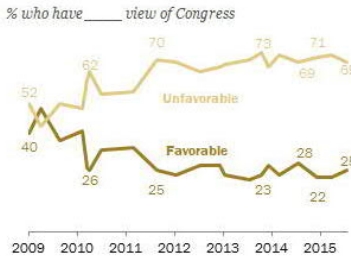
CIDEr (Vedantam et al., 2015) measures TF-IDF weighted n -gram overlaps between the model generated text and the reference. **BLEURT** (Selam et al., 2020) is a model-based metric that measures the fluency of the generated sentence and

the extent to which it conveys the meaning of the reference. We use BLEURT-base-128. **Content Selection or CS** score (Wiseman et al., 2017) measures how well the generated text matches the gold answer in terms of selecting which records to generate. Since both the BLEURT and CS are calculated at the sentence-level, we average these scores over the whole test set. Finally, we use **BERTScore** (Zhang et al., 2019) which correlates better with human judgments and has been widely adopted recently for text generation evaluation. BERTScore computes token similarity between the candidate and reference using contextualized embeddings rather than relying on exact matches.

Results As expected, the models perform better when only the relevant chart summary is given compared to when the entire article is provided (the first 2 setups in Table 2). The generative models have reduced performance due to the added texts in the article in setup 1. The extractive models also have a loss in performance in this setup mainly because they assume the answer comes from a single contiguous text segment whereas a gold answer can be constructed from multiple segments (Section 3.1). Specifically, these methods apply a sliding window over the tokens in the input sequence to find the start and end tokens of the answer span. However, if there are irrelevant tokens in the span, a window may miss portions of the answer that fall outside

Q1: Describe the change in favorability towards Congress.

Favorability Toward Congress Little Changed



Gold: Views of Congress continue to hover near record lows: Just 25% of Americans view Congress favorably.

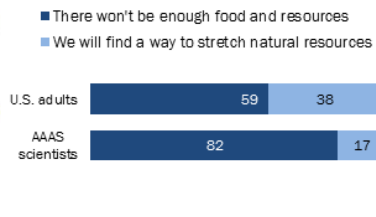
VLT5: 25% express a favorable opinion of Congress, while 69% view it unfavorably. But since April 2014, the share of Americans with a positive view of Congress has fallen off to 25%.

Bboxes-VLT5: A majority of the public (69%) has a favorable opinion of Congress, while 23% view it unfavorably. In July 2014, the balance of opinion was just the opposite: 47% expressed a favorable opinion of Congress, while 25% held an unfavorable view.

Q2: Describe the proportions of U.S. adults and AAAS scientists that think population growth won't be a problem.

Resources and Population Growth

% of each group saying the growing world population will or will not be a major problem because...



Gold: Just 17% of AAAS scientists and 38% of Americans said population growth won't be a problem because we will find a way to stretch natural resources.

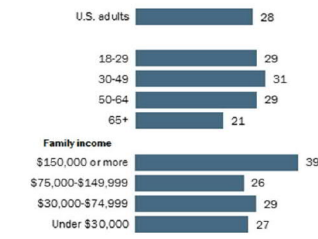
VLT5: Fully 59% of AAAS scientists say population growth will n't be a major problem because there will not be enough food and resources in the world, and 17% say we will find a way to stretch natural resources.

Bboxes-VLT5: Two-thirds of AAAS scientists say population growth will n't be a major problem because of scarce resources and other resources. At the same time, about six-in-ten of both groups say that the U.S. will find a way to stretch natural resources and hope that we will find a way to stretch these resources

Q3: How is the relation between family income and early technology adoption?

Younger men, higher-income adults prefer to be early technology adopters

% of U.S. adults with a strong preference for new technology products on a 6-item index



Gold: Adults with family incomes of at least \$150,000 annually tend to express a stronger preference for early technology adoption on this summary index (39% do so) compared with those at middle and lower income levels

VLT5: Younger men (39%) are more likely than older adults (26%) to express a strong preference for being early technology adopters.

Bboxes-VLT5: Older people in the U.S. tend to have higher levels of education and skills, rather than being early adopters. Many of those with higher incomes prefer early technology adoption; in fact, lower-income adults lag behind younger men in this regard.

Figure 3: Sample outputs from the Pew test set on VLT5 model (without summary provided). "Bboxes-" models use bounding box information of chart elements. Red indicates factual errors.

the maximum sequence length. Also, during training, the model rejects those instances where the answer span is not contained wholly inside the input sequence. The problem is worse with BERTQA because it uses a sequence length of 512 which is much shorter than the article size (1268 tokens on average), whereas ELECTRA uses a sequence length of 2048 tokens, reducing this effect.

We notice that the models perform better when the summary is provided compared to when only the chart is provided (setup 2 vs. 3 in Table 2). This is expected because when the summary is not given, the model does not have any textual reference to generate the answer to a given question. The extractive models BERTQA and ELECTRA achieve high ROUGE-L since they directly extract the text from the given summary to answer the question. ELECTRA performs better than BERTQA on all metrics except BLEU showing the benefit of the generator-discriminator based cascaded training.

When the summary is not provided, VLT5 achieves the best results across most measures, likely because it uses both visual and textual features to generate answers. On the contrary, CODR performs poorly possibly because it was originally intended for discourse generation whereas chart

QA is quite a different task. GPT-2 performs better than CODR but it has lower ROUGE-L and CS scores compared to BART and T5.

In order to better understand the dataset and how challenging the task is, we analyze the results of fine-tuning and testing T5 and VLT5, our best performing models with only the question Q or the summary S as input (see Table 3). In addition, we choose a naive baseline which randomly selects the answer from the given input text. This baseline spans 52% tokens of the input when only the summary S is given whereas it spans 7% tokens of the input when the article D is given (based on the statistics of tokens overlapping between the summary or article and the gold answer in our dataset(see Figure 2a)). As expected, we can see that both models struggle to answer the question when only the question is given as input. However, they perform better with only summary as input as the model has access to the summary containing the answer. In contrast, the performance drops when we use the baseline that randomly selects the answer, especially when the entire article is given as input as it becomes more difficult to randomly guess the answer.

We conduct several additional experiments to

Models	ROUGE_-F (1/2/L) ↑	CS ↑	BLEURT ↑	CIDEr ↑	BERTScore ↑	BLEU ↑
T5-Only Question	31.57/13.19/25.05	31.66%	-0.396	1.401	87.94	5.34
T5-Only Summary	67.56/63.78/65.47	82.22%	0.199	6.856	93.94	49.18
VLT5-Only Question	29.56/11.56/22.43	32.98%	-0.363	1.322	87.74	6.34
VLT5-Only Summary	67.31/63.54/ 65.79	77.47%	0.238	6.803	94.07	52.71
Random Summary Baseline	54.48/46.22/49.07	62.28%	-0.015	4.997	90.89	45.69
Random Article Baseline	23.95/8.81/17.12	19.66%	-0.641	0.960	84.36	5.50

Table 3: Results for T5 and VLT5 models with only the question or the summary as input on OpenCQA test set and a baseline that randomly selects 52% and 7% tokens for the with summary and with article setups respectively.

	Factual	Relevance	Fluency	Content Cov.	CS
VLT5	44.89%	86.67%	92.45%	41.11%	53.19%
VLT5-S	82.45%	88.67%	98.45%	85.12%	81.15%
Gold	96.45%	96.00%	98.89%	100.00%	100.00%
Krippendorff’s α	0.75	0.76	0.83	0.79	

Table 4: Human evaluation results for comparing between the outputs of VLT5 (without summary), VLT5-S (with summary) and the gold answer. The last row shows the agreements.

understand: (i) how performance may vary with respect to different chart types; (ii) how including the bounding box information as input impacts the performance; and (iii) how much the OCR-extracted text contributes to the output. Details of these experiments can be found in Appendix A.3.

5.2 Human Evaluation

To further assess the quality of the answers generated by the models, we performed a human study on 150 randomly sampled charts from our OpenCQA dataset with three internal annotators who are native speakers of English. For comparison, we chose the outputs from the best performing generative model (VLT5) on the with and without summary settings, which we denote as VLT5-S and VLT5, respectively. We also provide the gold answer (as control) and randomise the order of all three answers to remove biases. The annotators assess each answer based on three criteria adapted from (Yuan et al., 2021): (i) **Factual correctness** which measures the extent to which the generated text contains statements entailed by the source (*i.e.*, generated facts are supported by the chart), (ii) **Relevance** which measures how consistent the generated text is with respect to the question, (iii) **Fluency** which measures the extent to which the generated text is deficient of formatting issues, capitalization errors or ungrammatical sentences (*e.g.*, fragments, missing components) which would otherwise make the text difficult to read. For these three criteria, annotators provided a 5-point Likert scale rating from 1 (the worst) to 5 (the best).

We further propose a new *recall-oriented* criteria called **Content Coverage** which measures the extent to which the facts from the gold answer are cov-

ered by the generated text, ranging from 1 (0-20%) to 5 (80-100%). For this, the order of outputs of the two models were randomized to counterbalance any potential ordering effect. Each comparison was performed by three annotators. To measure inter-annotator reliability, we computed Krippendorff’s alpha (Krippendorff, 2011) and found a good overall agreement with an alpha coefficient of 0.806.

Table 4 shows the results of human evaluation, where for each model we show the percentage of answers that received the nearly perfect/perfect ratings (*i.e.*, 4 and 5). The gold answers receive high ratings across the first three measures which attests the quality of our dataset. VLT5-S achieves higher ratings across all measures than VLT5 as it has access to the summary. The VLT5 model also received impressive ratings on Relevance and Fluency while it has more room for improvement on Factual Correctness and Content Coverage, especially when the summary is not given. Lastly, we see that the automatic and the human evaluation measures for content coverage, *i.e.*, the CS score and Content Coverage, both of which are recall oriented, tend to be correlated.

5.3 Error Analysis and Challenges

We have manually analyzed the outputs from our best performing model to explain the key challenges that existing models face. Overall, the outputs of VLT5 model are often fluent and grammatically correct as evident from Figure 3. Also, this model rarely hallucinates and is often true to the source context. However, there are still several areas for improvement which we discuss below.

Factual Correctness and relevancy In Figure 3, both variants of VLT5 fail to associate some reported data values (highlighted in red) with their corresponding axis labels. In (Q3 in Figure 3), the VLT5 model outputs some facts about the relation between ‘age’ and ‘early technology adoption’ but the question asked about the relation with ‘family income’, not ‘age’. To address the factual errors and irrelevant facts, future models could create bet-

ter input representations including semantic graph representations (Teney et al., 2017) by extracting and exploiting relationships among the question, data values, chart elements (e.g., axis labels) and their visual features (e.g., colors).

Mathematical & Logical Reasoning Often gold answers include numerical reasoning to provide rich explanations. For example, in Figure 3(Q2), the gold answer provides a sense of limited proportion by mentioning “Just 17% of AAAS...”, which is not captured in the generated outputs. Future models may improve such numerical reasoning as an intermediate step before surface realization (Chen et al., 2020c). In another case (Q3 in Figure 3), the gold answer considers that incomes below 150k are middle and lower income levels which is not captured by models. Future work could infer such rich semantics with the help of external knowledge sources and inference based modelling (Bowman et al., 2015; Talmor et al., 2019).

Rare Topics We also observe that the VLT5 model tends to produce less fluent and factually correct answers when the sample comes from a rare topic (e.g., Bboxes-VLT5 in Q2 in Figure 3). Future work could focus on transfer learning and building more diverse datasets to handle such variations.

Automatic Evaluation It has been acknowledged that metrics like BLEU do not capture many data-to-text generation issues (Parikh et al., 2020). This is especially the case for open-ended questions where correct answers can be expressed in multiple possible ways. While we evaluated the models through several metrics, we urge for further research on building better automatic metrics that capture model performance in terms of factual correctness, relevancy and reasoning aspects while also correlating strongly with human judgements.

6 Conclusion

We propose a new benchmark, OpenCQA, for answering open-ended questions about charts using descriptive texts. We also introduce several state-of-the-art baselines and measures. Our evaluation suggests that current state of the art generative models can produce fluent text but still struggle to produce relevant and factually correct statements with numerical and logical reasoning. We hope that OpenCQA will serve as a useful research benchmark for model and metric development and motivate other researchers to explore this new task.

Ethical Considerations

During the dataset collection and annotation process, we had many ethical issues to take into consideration. To respect the intellectual property of the chart publishers, we only used publicly available charts from resources that provide publication rights of downloaded content for academic purposes. According to the terms and conditions for Pew,¹ users are allowed to use the content as long as they are attributed to the Center or are not attributed to a different party.

To fairly compensate the Mechanical Turk annotators, we compensated the annotators based on the minimum wage in the US (7.25 US\$ per hour), which is 1 US\$ for each task. Additionally, to protect the privacy of these annotators, all of their annotations were anonymized. To ensure the reproducibility of our experimental results, we have provided the hyperparameter settings in Appendix A.2.

We foresee one possible misuse of our models that is to spread misinformation. Currently, our model outputs tend to appear fluent but contain some factual errors, as detailed in Section 5.3. Hence, if such model outputs are published without being corrected, it may mislead and misinform the general public.

Limitations

A limitation of our dataset is that we were limited to Pew research (pewresearch.org) as a source due to the nature of our task and thus could not consider other sources. Future work could expand on our dataset when suitable sources become available. Further, we did not consider long-range sequence models such as linformer (Wang et al., 2020) or recently proposed memorized transformer (Wu et al., 2022) for modeling long sequences. Lastly, our task setup is limited since we only have access to the automatically extracted OCR data which is often noisy. Future methods can focus on improving OCR extraction for this task to improve the input of the model.

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¹<https://www.pewresearch.org/about/terms-and-conditions/>

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A Appendices

A.1 Data Collection & Annotation

A.1.1 Data Collection

We built our OpenCQA dataset based on the Chart-to-text benchmark constructed by [Kantharaj et al. \(2022b\)](#). We manually went over all the charts in this benchmark to retain 7,724 that we deemed suitable for our study. In particular, we filtered out samples that are too complex and samples which we could not make an open-ended question. Figure 5 shows examples of such samples.

In the Chart-to-text benchmark, each sample consists of a chart, the title, text extracted using an OCR method and associated summary text and the original article. OCR text segments were extracted top to bottom left to right along with their rectangular bounding boxes given as $\{x,y,len(x),len(y)\}$. The extracted title from the chart image was taken as the final chart title if there was no associated `alt` text with the chart image. If the `alt` text (which gives a short chart description) was available, the longer of the two was taken by comparing it with the extracted title. The summary for each chart was obtained by finding the most relevant texts to the chart following an annotation process which is described in detail in ([Kantharaj et al., 2022b](#)).

A.1.2 Data Annotation

In each HIT (Human Intelligent Task), the worker answered three questions previously asked by another coworker for three separate charts respectively and also created three new question-answer pairs for three new charts (see figure 8). The first round of 30 samples were created by the authors but were not included in the final dataset to remove any potential bias. Each subsequent round of samples were created by crowdworkers who would answer existing question that were created in the previous round while also creating new question-answer pairs for the next round.

Each participant was first provided with a consent form where the complete procedure of the study and data collection was explained. Once the participant provided consent, detailed instructions were shown on how to complete the task(see Figure 9). In particular, participants were instructed to create open-ended questions that required a descriptive answer. An answer was considered to be descriptive if it was at least one sentence long and derivable from the chart(*i.e.*, it did not refer to

any knowledge outside the data represented in the chart). This method of selecting the answer for the question from the summary is very controlled since the summary was written by a professional writer and these summaries usually had good linguistic style and grammatical structure. Participants were additionally shown sample question-answer pairs to explain how ideal questions looked like (see Figure 10).

To ensure quality, only participants with a hit approval rate greater than 95% and over 5,000 approved hits were selected for pre-screening. In the pre-screening stage, participants completed a sample task that allowed us to assess their proficiency for this study. Those who successfully completed the task according to the given instructions were qualified for participating in the main study. The study protocol was approved by the ethics review board at York University with certificate ID e2021-317.

A.2 Baseline Models

The architectures of different example models along with sample inputs and outputs are shown in Figure 4. All models concatenate the question, title and OCR extracted data and additionally the summary/article based on the problem setting. Due to the long length of articles, the model inputs are often truncated to accommodate the maximum sequence length. On average 68% of the answer is contained in the truncated input to the model. We provide more details on the hyperparameter settings for different models below.

GPT2 We fine-tune GPT2 with a batch size of 6 for 5 epochs with a max input sequence length of 512 tokens and output sequence length of 128 tokens.

BERTQA We fine-tune BERT-large (340M parameters, 24 layers) with a batch size of 4 for 2 epochs, with a max input sequence length of 512 tokens and output sequence length of 128 tokens.

CODR We fine-tune BART-large for 10 epochs and a batch size of 6 with max input sequence length of 512 tokens, output sequence length of 128 tokens,gradient accumulation set to 1 and the other parameters at default settings.

BART We fine-tune BART-Base² (140M, 6-layers) with max input sequence length of 512 to-

²huggingface.co/transformers

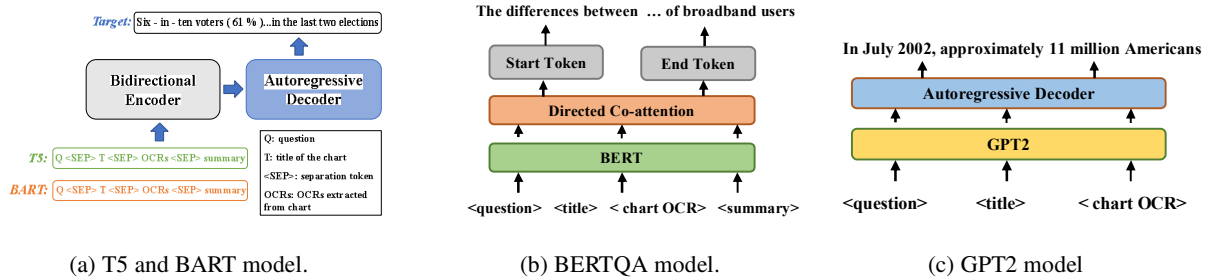


Figure 4: Examples of model architectures that show the fine-tuning step of the training stage with sample inputs and outputs. (a) and (b) show examples of inputs and outputs from models when the summary is given. (c) show examples of inputs and outputs of GPT2 (when the summary is not given as input). Here, BERTQA is an extractive model, others are generative models.

kens, for 50K iterations with a batch size of 4 and evaluate after every 1,000 iterations on the validation set. The initial learning rate is set to 0.00005. For inference, we use the model with the lowest validation loss and decode with a beam size of 4.

T5 Similar to BART, we fine-tune T5-Base² (220M, 12-layer Transformer as the encoder and decoder) with max input sequence length of 512 tokens, for 100k iterations with a batch size of 4 and an initial learning rate of 0.00001, evaluate after every 1,000 iterations on validation set, and use the model with best validation loss for testing. Inference is done with beam search with a beam size 4.

VLT5 We fine-tune the pretrained VLT5 (T5-base as its backbone) for 100 epoches with a learning rate of 0.0001 and max input sequence length of 512 tokens. Inference is done with beam search with a beam size of 4. Note that the original VL-T5 represents an input image with 36 object regions. However, since the number of bounding-box objects in charts varies from one to another, we either pad the extracted visual features (with zeros) or truncate them to maintain the length at 36.

Electra We fine-tune Electra-Base for 25,000 iterations with a batch size of 4 and initial learning of 0.0001. The max sequence size of input is set to 2048. For inference, the batch size is set to 4 with search beam size of 20.

A.3 Additional Results from Evaluation

A.3.1 Performance by Chart Types

We analyze the performance by chart types in Table 7. We observe that our best performing models perform better at summarizing simple (pie charts) and frequent chart types (bar charts), whereas the performance generally decreases for complex and less frequent charts (e.g., scatter plots).

A.3.2 Ablation Test

In table 5 we show the results of an ablation test, where each model is given the question and OCR-extracted chart data as input. Here, models with "Bboxes" prefix are given the bounding boxes C_{bbox} of text segments in the chart, and the other models are repeated here from Table 2 for comparison. We observe that the inclusion of the bounding box information does not necessarily improve the performance. One possible reason could be that bounding box extraction of the OCR model is not always perfect as the model sometimes merges or splits the bounding boxes incorrectly. Note that for ROUGE-F evaluation we used the python package rouge-score, which is a Google re-implementation of the original Rouge-1.5.5 perl script.

A.3.3 The Effect of the OCR-text

We further analyze how the model extracts the answer from different input sources (e.g., input summary vs. OCR-generated text). For this purpose, we consider three new metrics for Chart Extraction Factor (CEF) scores as follow:

CEF-Precision: Shows how much fraction of generated tokens in the answer (excluding stopwords)

Models	Type	ROUGE_-F (1/2/L) ↑	CS ↑	BLEURT ↑	CIDEr ↑	BERTScore ↑	BLEU ↑
Setup 1: With Article Provided							
Bboxes-BERTQA	Extractive	23.95/9.17/16.69	32.71%	-0.736	1.080	85.10	9.35
Bboxes-ELECTRA	Extractive	52.12/43.07/47.49	49.74%	-0.051	4.379	89.97	30.77
Bboxes-BART	Generative	45.07/31.93/39.55	48.48%	-0.108	3.411	90.20	16.78
Bboxes-T5	Generative	66.21/60.15/63.40	67.49%	0.076	5.414	93.55	41.58
BBoxes-VLT5	Generative	55.91/46.53/51.76	62.05%	0.048	4.932	91.83	37.94
Bboxes-GPT2	Generative	16.78/6.89/14.08	15.45%	-0.757	0.85	81.12	1.36
Bboxes-CODR	Generative	13.67/0.97/10.88	1.73%	-1.026	0.035	82.40	0.00
BERTQA	Extractive	22.81/8.53/16.63	28.17%	-0.692	0.983	85.00	9.58
ELECTRA	Extractive	57.67/50.09/53.89	54.73%	0.066	5.100	91.01	38.79
BART	Generative	50.68/38.95/45.55	54.29%	-0.017	4.121	91.08	23.91
T5	Generative	66.57/60.40/ 63.46	68.24%	0.103	5.437	93.53	41.28
VLT5	Generative	58.90/49.97/54.82	66.06%	0.076	5.227	92.34	40.06
GPT2	Generative	16.71/66.57/13.75	14.71%	-0.745	0.814	82.05	0.99
CODR	Generative	14.58/1.31/11.37	3.4%	-1.155	0.051	81.90	0.43
Setup 2: With Summary Provided							
Bboxes-BERTQA	Extractive	71.76/68.56/70.13	85.25%	0.309	7.216	94.73	67.24
Bboxes-ELECTRA	Extractive	75.87/73.78/75.09	91.93%	0.367	7.766	95.98	65.17
Bboxes-BART	Generative	63.11/57.22/60.44	65.93%	0.205	6.090	93.23	36.12
Bboxes-T5	Generative	76.54/74.24/75.35	84.21%	0.377	7.780	95.36	60.26
BBoxes-VLT5	Generative	73.91/71.07/72.67	80.92%	0.341	7.470	94.98	58.25
Bboxes-GPT2	Generative	18.21/15.41/17.47	25.73%	-0.686	1.955	43.28	16.06
Bboxes-CODR	Generative	12.16/0.73/9.31	2.040%	-1.283	0.046	80.17	0.19
BERTQA	Extractive	70.97/67.77/69.34	85.28%	0.297	7.177	94.65	66.33
ELECTRA	Extractive	76.24/74.33/ 75.48	92.57%	0.378	7.823	96.06	65.40
BART	Generative	66.41/61.86/64.41	68.71%	0.257	6.613	93.85	38.42
T5	Generative	75.77/73.51/74.51	81.73%	0.369	7.728	95.22	57.93
VLT5	Generative	75.07/72.35/73.86	85.36%	0.376	7.597	95.20	59.80
GPT2	Generative	14.29/11.13/13.42	22.00%	-0.782	1.725	49.18	12.68
CODR	Generative	13.81/0.76/10.25	2.480%	-1.039	0.038	81.87	0.31
Setup 3: Without Summary Provided							
Bboxes-BART	Generative	39.79/21.24/31.94	49.12%	-0.171	2.254	89.63	7.40
BBoxes-T5	Generative	40.88/21.86/32.96	51.12%	-0.181	2.339	89.56	9.09
BBoxes-VLT5	Generative	42.62/22.18/32.93	53.26%	-0.132	2.382	89.52	14.01
Bboxes-GPT2	Generative	28.57/10.91/22.24	31.30%	-0.459	1.246	84.50	3.92
Bboxes-CODR	Generative	14.18/1.19/10.22	4.43%	-1.053	0.053	81.77	0.22
BART	Generative	40.29/21.40/32.48	49.07%	-0.166	2.260	89.69	7.41
T5	Generative	41.12/22.09/32.97	52.30%	-0.173	2.357	89.59	9.28
VLT5	Generative	42.87/22.60/ 33.29	54.47%	-0.134	2.447	89.53	14.73
GPT2	Generative	28.55/11.26/22.46	32.00%	-0.493	1.314	85.05	4.89
CODR	Generative	14.67/1.05/10.90	4.14%	-1.170	0.053	81.86	0.32

Table 5: Ablation study results for understanding the effect of including the OCR extracted bounding boxes as input. All models use OCR-extracted data as input. "Bboxes-" models use bounding box information of chart elements.

Models	CEF-Precision ↑	CEF-Recall ↑	CEF-Coverage ↑
Test	49.32	25.89%	47.34
Setup 1: With Article Provided			
Bboxes-VLT5	38.05%	21.16%	42.18%
VLT5	42.32%	22.57%	43.11%
Bboxes-T5	42.82%	22.63%	43.60%
T5	42.50%	24.31%	45.30%
Setup 2: With Summary Provided			
Bboxes-VLT5	42.94%	25.18%	46.71%
VLT5	43.48%	25.15%	46.96%
Bboxes-T5	42.53%	25.78%	47.74%
T5	42.04%	26.96%	49.06%
Setup 3: Without Summary Provided			
Bboxes-VLT5	48.70%	22.46%	43.54%
VLT5	50.18%	23.09%	44.08%
Bboxes-T5	60.71%	20.36%	38.50%
T5	61.89%	21.24%	40.32%

Table 6: Chart Extraction Factor (CEF) scores for VLT5 and T5 across all problem setups. "Bboxes-" models use bounding box information of chart elements.

A is coming from OCR-extracted text segments C_{label} .

CEF-Coverage: Represents how much fraction of OCR-extracted text segments C_{label} contribute to the generated answer A . An OCR-extracted text segment contributes to the answer if any generated tokens in the answer A appear in the segment.

CEF-Recall: Shows how much fraction of OCR tokens in C_{label} is recalled in answer A .

The results on our top performing models are shown in Table 6. We observe that the CEF-Precision score decreases across all models when the summary or the article is given as input compared to the setup where only the OCR text is given. This suggests that the model utilizes less information from the extracted OCR text when it has access to summary or article. In contrast, CEF-Coverage scores tend to increase when the summary is provided in comparison to without summary as the answer tends to cover more OCR text segments

VLT5 (Without Summary)						
	Bar	Line	Pie	Area	Scatter	
ROUGE ↑	43.75/23.41/33.96	39.86/19.82/30.64	48.18/26.12/39.12	100.0/100.0/100.0	31.89/9.21/19.33	
BLEURT ↑	-0.134	-0.150	-0.020	0.800	-0.329	
CIDEr ↑	2.576	2.058	2.912	0.0	1.181	
BERTScore ↑	89.60	89.21	90.86	98.79	86.35	
VLT5 (With Summary)						
	Bar	Line	Pie	Area	Scatter	
ROUGE ↑	75.61/72.9/74.38	73.19/70.46/71.93	80.1/77.57/79.48	100.0/100.0/100.0	67.46/66.83/67.46	
BLEURT ↑	0.381	0.353	0.457	0.800	0.302	
CIDEr ↑	7.657	7.414	7.920	0.0	7.378	
BERTScore ↑	95.28	94.87	96.24	98.79	93.47	

Table 7: Results of VLT5 (without summary) and VLT5 (with summary) on our test set *w.r.t.* chart types.

Question Validation & Editing	Disagreement Resolution	Decontextualization
<p>Describe the concerns on mobile phones additions among the surveyed countries?</p> <p>Widespread concern about mobile phones' impact on children across 11 emerging economies surveyed</p> <p><small>% of adults who say people should be very/somewhat/not concerned about when using their mobile phones</small></p>	<p>Ans 1: In addition to their concerns about the impact of mobile phones on children, majorities across the 11 countries surveyed also say people should also be very worried about issues such as identity theft (an 11-country median of 66% say people should be very concerned about this), exposure to false information (64%) addiction (62%) and harassment or bullying (59%) when using their mobile phones face-to-face due to mobile phone use (48%)</p> <p>Ans 2: the impact of mobile phones on children, majorities across the 11 countries surveyed also say people should also be very worried about issues such as identity theft (an 11-country median of 66 % say people should be very concerned about this), mobile phone addiction (62%) and harassment or bullying (59%) when using their mobile phones</p>	<p>In addition to their concerns about the impact of mobile phones on children, majorities across the 11 countries surveyed also say people should also be very worried about issues such as identity theft (an 11-country median of 66% say people should be very concerned about this), exposure to false information (64%), mobile phone addiction (62%) and harassment or bullying (59%) when using their mobile phones. Fewer are very concerned about the risk that people might lose the ability to communicate face-to-face due to mobile phone use (48%).</p>

Table 8: Illustration of data annotation process (steps 2 - 4). Green text is newly added from the summary, **strikeout red** text is removed. Purple text is from the first worker, blue text is from the second worker, and brown represents texts in common between the participants.

if the summary is present. The CEF-recall scores increase when the summary is provided since many tokens in the summary overlap with the OCR extracted text. Table 9 illustrates an example of how OCR-extracted texts and the input summary contributed to the answer.

A.3.4 Human Evaluation

The user interface for the human evaluation annotation task of comparing among generated answers by different models are given in Figure 11.

A.3.5 Additional Sample Outputs

Additional sample outputs from the best performing model are shown in Figure 7.

A.3.6 Additional Related Work

Query Focused Summarization In this task, the goal is to generate a summary of the text document(s) based on a given query. For abstractive summarization, a key challenge is that there are only a few small datasets on specific domains such as news (Dang, 2005) debate (Nema et al., 2017) and meeting (Zhong et al., 2021). Given

the lack of large training data, some prior methods (Baumel et al., 2018; Laskar et al., 2020; Pasunuru et al., 2021) focus on applying transfer learning techniques to first pretrain on a large generic summarization dataset and then finetune on a specific query focused summarization task. However, these models are not designed to incorporate visual features of charts and their target texts are quite different than ours, as we focus on generating data insights with logical reasoning aspects.

Model Input	Generated Answer
<p>Question: What are the partisans views on whether the marches will increase public support for science?</p>	<p>OCR extracted data: Americans are divided over whether the science marches will help or make no difference to public support for science. 44% of U.S. adults who say the protests, marches and demonstrations public about science held this April will help public support for science. 44% think they will make no difference. 7% think they will hurt public support. Most Democrats and Democratic leaners (61%) believe the marches and demonstrations held in April will benefit public support for science. By contrast, just 22% of Republicans and independents who lean to the GOP say the marches will help drive public support for science, while six-in-ten (60%) of this group believes the marches will have no impact on public support and 13% say the marches will hurt public support.</p> <p>Summary: Americans are closely divided on the issue of whether the marches will increase public support for science: 44% think they will help and 44% think they will make no difference. Another 7% believe they will hurt public support. Most Democrats and Democratic leaners (61%) believe the marches and demonstrations held in April will benefit public support for science. By contrast, just 22% of Republicans and independents who lean to the GOP say the marches will help drive public support for science, while six-in-ten (60%) of this group believes the marches will have no impact on public support and 13% say the marches will hurt public support.</p>

Table 9: Illustration of chart extraction scoring. Green text are answer tokens generated from OCR text, Blue text are answer tokens not found in OCR text but generated from summary, Red text highlights the remaining OCR-extracted text. All text sequences in the chart with bounding boxes are extracted by the OCR model and Green bounding boxes are used in the generated answer. CEF(Recall): 43.48; CEF(Coverage): 86.36; CEF(Precision): 54.54.

(1) Too Complex	(2) Cannot Create Open Ended Question	(3) Good																																																																																																																																																						
	<p>Internationally, U.S. Stands in Middle of Pack on Science, Math Scores</p> <p>Average scores of 15-year-olds taking the 2012 Program for International Student Assessment</p> <table border="1"> <thead> <tr> <th colspan="3">MATHEMATICS</th> <th colspan="3">SCIENCE</th> </tr> </thead> <tbody> <tr> <td>Singapore</td><td>573</td><td>Russian Fed.</td><td>429</td> <td>Hong Kong</td><td>555</td><td>Luxembourg</td><td>521</td> </tr> <tr> <td>Hong Kong</td><td>553</td><td>Sweden</td><td>429</td> <td>Singapore</td><td>553</td><td>Costa Rica</td><td>428</td> </tr> <tr> <td>Taiwan</td><td>550</td><td>United States</td><td>411</td> <td>Japan</td><td>547</td><td>Portugal</td><td>423</td> </tr> <tr> <td>South Korea</td><td>544</td><td>Lithuania</td><td>410</td> <td>Finland</td><td>545</td><td>Russian Fed.</td><td>423</td> </tr> <tr> <td>Mexico</td><td>538</td><td>Sweden</td><td>410</td> <td>Canada</td><td>541</td><td>Sweden</td><td>423</td> </tr> <tr> <td>Japan</td><td>536</td><td>Hungary</td><td>410</td> <td>South Korea</td><td>538</td><td>Iceland</td><td>416</td> </tr> <tr> <td>Liechtenstein</td><td>535</td><td>Croatia</td><td>410</td> <td>Vietnam</td><td>538</td><td>Slovakia</td><td>413</td> </tr> <tr> <td>Switzerland</td><td>531</td><td>Israel</td><td>408</td> <td>Poland</td><td>535</td><td>Israel</td><td>410</td> </tr> <tr> <td>Netherlands</td><td>525</td><td>Greece</td><td>403</td> <td>Liechtenstein</td><td>535</td><td>Greece</td><td>407</td> </tr> <tr> <td>Estonia</td><td>521</td><td>Serbia</td><td>403</td> <td>Canada</td><td>535</td><td>Turkey</td><td>403</td> </tr> <tr> <td>Finland</td><td>519</td><td>Turkey</td><td>403</td> <td>Germany</td><td>534</td><td>U.A.C.</td><td>403</td> </tr> <tr> <td>Poland</td><td>518</td><td>France</td><td>403</td> <td>Taiwan</td><td>533</td><td>Bulgaria</td><td>403</td> </tr> <tr> <td>Canada</td><td>518</td><td>Greece</td><td>403</td> <td>Netherlands</td><td>532</td><td>Serbia</td><td>403</td> </tr> <tr> <td>Belgium</td><td>515</td><td>Bulgaria</td><td>403</td> <td>Ireland</td><td>532</td><td>Chile</td><td>403</td> </tr> <tr> <td>Germany</td><td>514</td><td>U.A.R.</td><td>403</td> <td>Mexico</td><td>531</td><td>Thailand</td><td>403</td> </tr> </tbody> </table>	MATHEMATICS			SCIENCE			Singapore	573	Russian Fed.	429	Hong Kong	555	Luxembourg	521	Hong Kong	553	Sweden	429	Singapore	553	Costa Rica	428	Taiwan	550	United States	411	Japan	547	Portugal	423	South Korea	544	Lithuania	410	Finland	545	Russian Fed.	423	Mexico	538	Sweden	410	Canada	541	Sweden	423	Japan	536	Hungary	410	South Korea	538	Iceland	416	Liechtenstein	535	Croatia	410	Vietnam	538	Slovakia	413	Switzerland	531	Israel	408	Poland	535	Israel	410	Netherlands	525	Greece	403	Liechtenstein	535	Greece	407	Estonia	521	Serbia	403	Canada	535	Turkey	403	Finland	519	Turkey	403	Germany	534	U.A.C.	403	Poland	518	France	403	Taiwan	533	Bulgaria	403	Canada	518	Greece	403	Netherlands	532	Serbia	403	Belgium	515	Bulgaria	403	Ireland	532	Chile	403	Germany	514	U.A.R.	403	Mexico	531	Thailand	403	<p>Crime Tops List of Problems in Mexico</p> <p>Percent saying ___ is a very big problem</p> <table border="1"> <tbody> <tr><td>Crime</td><td>79%</td></tr> <tr><td>Corrupt political leaders</td><td>72</td></tr> <tr><td>Drug cartel-related violence</td><td>72</td></tr> <tr><td>Water pollution</td><td>70</td></tr> <tr><td>Air pollution</td><td>69</td></tr> <tr><td>Corrupt police officers</td><td>63</td></tr> <tr><td>Safety of food</td><td>58</td></tr> <tr><td>Health care</td><td>54</td></tr> <tr><td>Poor quality schools</td><td>52</td></tr> <tr><td>People leaving for jobs in other countries</td><td>38</td></tr> <tr><td>Traffic</td><td>33</td></tr> <tr><td>Electricity shortages</td><td>31</td></tr> </tbody> </table>	Crime	79%	Corrupt political leaders	72	Drug cartel-related violence	72	Water pollution	70	Air pollution	69	Corrupt police officers	63	Safety of food	58	Health care	54	Poor quality schools	52	People leaving for jobs in other countries	38	Traffic	33	Electricity shortages	31
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<p>Historically, there have been modest differences between generational groups in trust in government and that remains the case today. Currently, 19% of Millennials (now ages 23-38) report trusting the government, similar to the shares of older generations who say the same. Trust in government remains at or near historically low levels across generational lines.</p>	<p>Fact Tank's look at standardized test results around the world seemed to bear out these sentiments: U.S. students are improving – slowly – in math and science, but still lagging their peers internationally.</p>	<p>About six-in-ten (58%) say food safety is a very big problem, and 54% say the same about health care. Roughly four-in-ten or fewer are troubled by people leaving for jobs in other countries (38%), traffic (33%) and electricity shortages (31%).</p>																																																																																																																																																						

Figure 5: Examples of charts in the Pew dataset: (1) too complex since the line charts are difficult to separate; (2) not suitable for creating an open-ended question since summary does not refer to information in the chart; and (3) a good sample consisting of a chart and the summary that refers to the chart information. We filter out samples like (1) and (2) from our dataset.

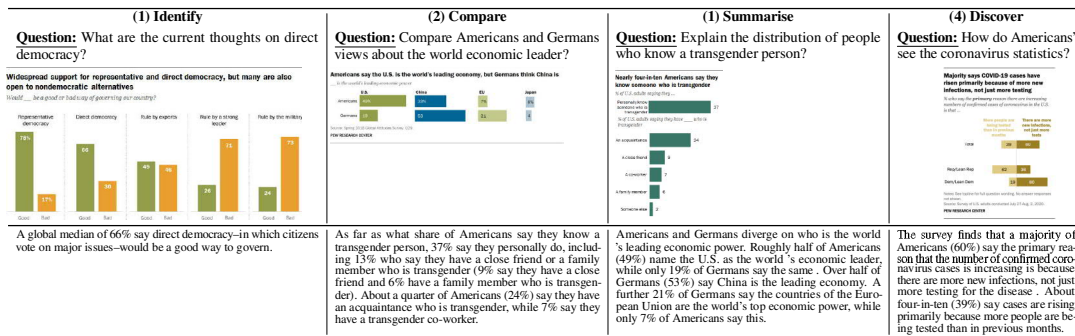


Figure 6: Examples question types in the Pew dataset: (1) Identify: The question refers to a specific target ('direct democracy') which represents a group of bars in the chart; (2) Compare: The question requires a comparison between two specific targets in the chart (e.g. between 'Americans' and 'Germans' which represent two groups of bars); (3) Summarize: The question asks to summarize the distribution statistic in the chart (i.e., 'people who know a transgender person'); (4) Discover: The question does not specify any specific statistical task but requires the inference and reasoning over the whole chart to derive key insights (e.g., majority of Americans say that the increase in coronavirus cases is due to more new infections, not just because of more testing).

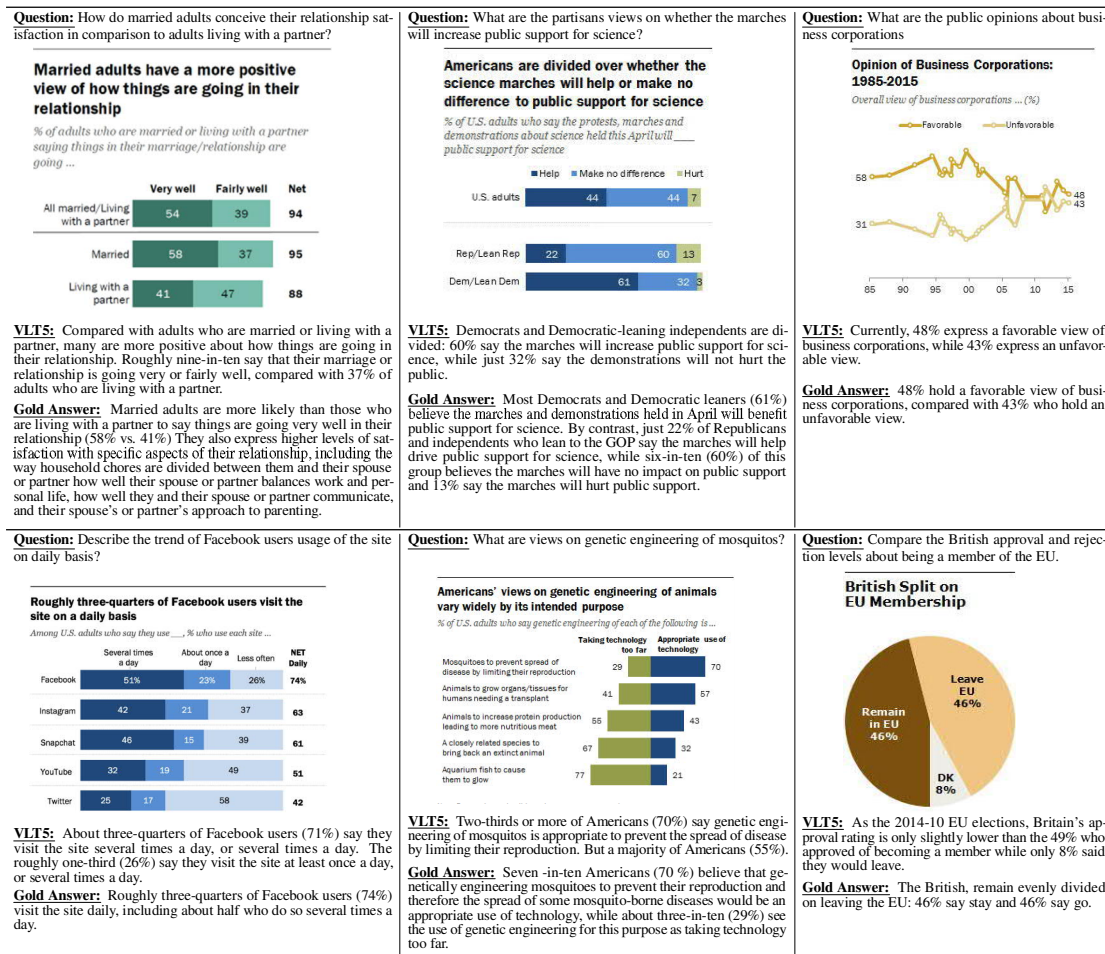


Figure 7: Sample outputs from the best performing model VLT5 (without summary).

Foreign-born population in the United States, 1850-2018

Foreign-born population, in millions

Year	Population (millions)
1850	2
1875	5
1900	10
1925	14
1950	11
1975	10
2000	20
2018	44.8

Question

How do foreigners in America compare in number to citizens?

Select your answer for the question above from the summary below

The foreign-born population residing in the U.S. reached a record 44.8 million, or 13.7% of the U.S. population, in 2018. This immigrant population has more than quadrupled since the 1960s, when the 1965 Immigration and Naturalization Act took effect. Though growth has begun to slow in recent years, the number of immigrants living in the United States is projected to almost double by 2065.

Clear Selection

(a) The interface shows a sample where the question is given and the crowdworker needs to highlight the corresponding answer from the summary.

Revenue for Univision network

Total revenue (in U.S. dollars)

Year	Revenue (billions)
2014	3.0
2015	2.9
2016	3.1
2017	3.0
2018	2.8

Question

Describe the financial situation of Univision?

Select your answer for the question above from the summary below

Univision's total revenue remained steady at slightly less than \$3 billion in 2018. (Telemundos revenue is not available for analysis, as its parent company, Comcast, does not provide network-specific revenue.)

Clear Selection

(b) The interface shows the highlighted answer selected by the user for a given question.

Home broadband use over time

% of U.S. adults who are home broadband users

Year	Percentage (%)
2002	5
2004	15
2006	35
2008	55
2010	65
2012	70
2014	75
2016	70
2018	75

Create a question about the chart

Write a question for which the answer is in the summary.

Select your answer for the question above from the summary below

The proportion of American adults with high-speed broadband service at home increased rapidly between 2000 and 2010. In recent years, however, broadband adoption growth has been much more sporadic. Today, roughly three-quarters of American adults have broadband internet service at home.

Clear Selection

(c) The interface shows an annotation task, where the annotator needs to formulate a new question and then subsequently select the answer from the summary paragraph.

Figure 8: Amazon Mechanical Turk study interface.

For each given chart, there is a corresponding summary that discusses about the data in the chart. For each of the first 3 charts the question is already given and you need to highlight the corresponding answer from the summary. For each of the next 3 charts you must create an open ended question for which the answer lies in the summary. Then, you should highlight the corresponding answer from the summary. At anytime you can deselect a word from the selected answer by clicking on it. You can also clear the whole selection by clicking the 'clear selection' button.

Answer Selection Criteria

- The answer should be atleast one sentence long
- It should provide a descriptive answer to the question asked. For example, 'Describe the distribution of non-English speakers among immigrants of U.S?' requires a textual description whereas 'What percentage of immigrants speak Arabic?' requires just a number as an answer.
- The answer should not reference any knowledge outside the data represented in the chart

Question Creation Criteria

- The question should be open ended and require a descriptive answer
- The descriptive answer of the chart should answer the question

Figure 9: Amazon Mechanical Turk Instructions for Mturk workers.

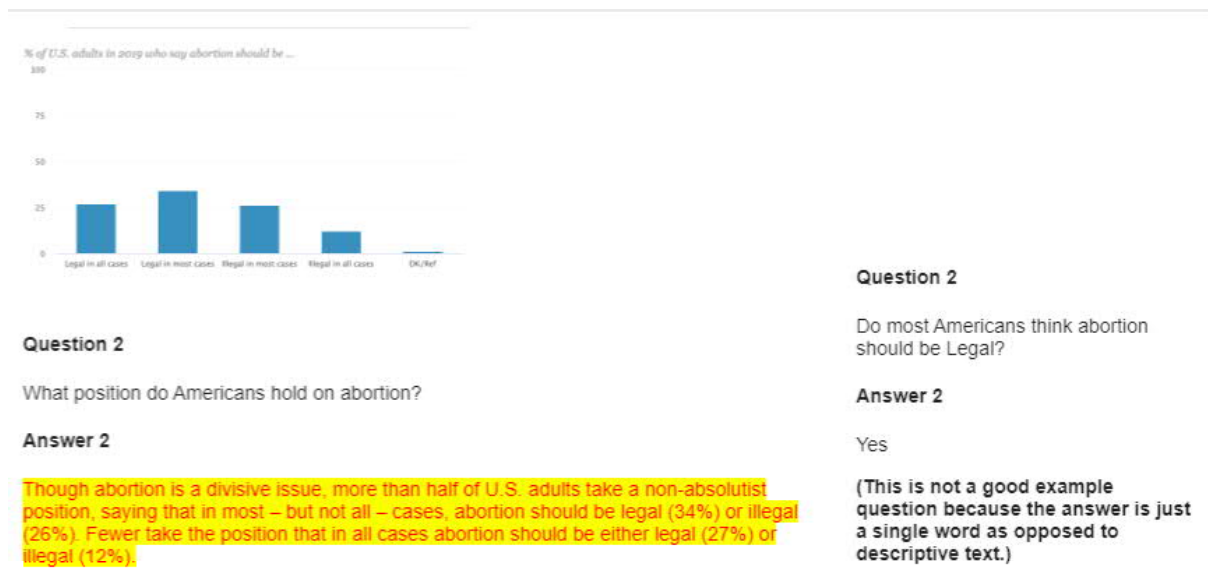


Figure 10: Example of good and bad open ended question and answer pair on Amazon Mechanical Turk(The question on the left is a good example since it requires a descriptive answer and is open ended, and the question on the right is a bad example as it is not open ended).

Model Evaluation

[View Instructions](#) [Load Progress](#) [Save Progress](#) Chart No. 0

Chart

Title: Merkel gets higher ratings globally than Xi, Putin or Trump
Confidence in to do the right thing regarding world affairs

Question: What opinion do the publics have about worldwide national leaders during the Trump government?

Merkel gets higher ratings globally than Xi, Putin or Trump

Confidence in ... to do the right thing regarding world affairs

	Confidence	No confidence	Don't know
Angela Merkel	42%	31%	18%
Xi Jinping	26%	63%	11%
Vladimir Putin	27%	68%	11%
Donald Trump	22%	74%	8%

Note: Percentages are global medians based on 37 countries. Xi not asked in Turkey.
Source: Spring 2017 Global Attitudes Survey.
PEW RESEARCH CENTER

Answers

Answer #1

Angela Merkel is the only world leader included in the survey who receives more positive than negative reviews. Across the 37 nations polled, a median of 42% express confidence in her, while 31% say they lack confidence. Ratings for Chinese President Xi Jinping and Russian President Vladimir Putin are mostly negative, and Trump receives even more unfavorable assessments than both of them.

Answer #2

Globally, a median of 42% voice confidence in Merkel to do the right thing when it comes to Trump.

Answer #3

Trump gets more negative ratings globally than Merkel, Xi or Putin. German Chancellor Angela Merkel is the only world leader included in the survey who receives more positive than negative reviews. Across the 37 nations polled, a median of 42% express confidence in her, while 31% say they lack confidence.

Evaluation Questions

Answer #1

How factually correct is the answer (facts mentioned are supported by the chart)? 1 2 3 4 5

How relevant is the answer to the query? 1 2 3 4 5

How fluent/grammatical is the answer? 1 2 3 4 5

Answer #2

How factually correct is the answer (facts mentioned are supported by the chart)? 1 2 3 4 5

How relevant is the answer to the query? 1 2 3 4 5

How fluent/grammatical is the answer? 1 2 3 4 5

Answer #3

How factually correct is the answer (facts mentioned are supported by the chart)? 1 2 3 4 5

How relevant is the answer to the query? 1 2 3 4 5

How fluent/grammatical is the answer? 1 2 3 4 5

[Submit](#)

(a) The interface for human evaluation that shows the gold answer as well as the outputs from VLT5 (VLT5 without summary) and VLT5-S (VLT5 with summary) in random order. The factuality, relevance and fluency measures are rated on a 5-point likert scale.

Model Evaluation

[View Instructions](#) [Load Progress](#) [Save Progress](#) Chart No. 0

Chart

Title: Merkel gets higher ratings globally than Xi, Putin or Trump
Confidence in to do the right thing regarding world affairs

Question: What opinion do the publics have about worldwide national leaders during the Trump government?

Merkel gets higher ratings globally than Xi, Putin or Trump

Confidence in ... to do the right thing regarding world affairs

	Confidence	No confidence	Don't know
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Donald Trump	22%	74%	8%

Note: Percentages are global medians based on 37 countries. Xi not asked in Turkey.
Source: Spring 2017 Global Attitudes Survey.
PEW RESEARCH CENTER

Answers

Gold Standard

Angela Merkel is the only world leader included in the survey who receives more positive than negative reviews. Across the 37 nations polled, a median of 42% express confidence in her, while 31% say they lack confidence. Ratings for Chinese President Xi Jinping and Russian President Vladimir Putin are mostly negative, and Trump receives even more unfavorable assessments than both of them.

Answer #1

Globally, a median of 42% voice confidence in Merkel to do the right thing when it comes to Trump.

Answer #2

Trump gets more negative ratings globally than Merkel, Xi or Putin. German Chancellor Angela Merkel is the only world leader included in the survey who receives more positive than negative reviews. Across the 37 nations polled, a median of 42% express confidence in her, while 31% say they lack confidence.

Evaluation Questions

Answer #1

To what extent the facts from the gold are covered by the answer? 0-20% 20-40% 40-60% 60-80% 80-100%

Answer #2

To what extent the facts from the gold are covered by the answer? 0-20% 20-40% 40-60% 60-80% 80-100%

[Submit](#)

(b) The interface for human evaluation on the content selection measure. The human compares between the gold answer and the outputs from VLT5 (VLT5 without summary) and VLT5-S (VLT5 with summary) presented in random order.

Figure 11: Human evaluation interfaces.